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Shared features and similarity : implications for category specificity and normal recognition

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SHARED FEATURES AND SIMILARITY:

IMPLICATIONS FOR CATEGORY SPECIFICITY AND NORMAL RECOGNITION

By

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ABSTRACT

Patients with category-specific visual agnosia (CSVA) often exhibit a disproportionate difficulty recognizing objects from biological categories due (in part) to the fact that exemplars from biological categories tend to be visually and conceptually more similar. Similarity is often conceived of as a pairwise property (i.e., in terms of distance in a psychological space matrix), but may be more accurately conceived of as a setwise property (i.e., in terms of shared features). The purpose of this study is to examine the effect of shared features on similarity in normal observers, while controlling for distance in structural space. Behavioral and electrophysiological results are presented that indicate that feature integration is necessary across a variety of tasks and that setwise properties (i.e., shared features) influence similarity. As such, it is suggested that future studies conceptualize similarity in terms of setwise (and not pairwise) object properties.

Approval Page

I certify that I have read this thesis and find that, in scope and quality, it satisfies the requirements for the degree of Master of Arts/Master of Science.

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GENERAL INTRODUCTION

What do we mean when we describe things as similar? Are those qualities that allowed Shakespeare to inquire whether a Summer's day is in some way comparable to youth and beauty the same that cause us to reach for the wrong suitcase at the airport baggage claim? Everyday each of us makes hundreds (if not thousands) of discriminations between similar objects (Which car is mine? Is that my cell phone or yours? Is that the person I'm meeting for lunch?), and yet this process is so automatic we give it little thought. Our ability to discriminate between objects that are often quite similar (e.g., hostile vs. friendly faces) is integral to our survival and presumably a quite primitive skill, but how do we manage such a feat? What qualities are hidden in the images that dance across our retinas that allow us to perceive both the qualities of a mother's smile in her baby's eyes and dragons in passing clouds?

Generally speaking, the more similar two objects are to one another the more often they will be confused. But, saying that similarity is gauged by confusability does not address the fundamental issue: What qualities do similar objects possess that dissimilar objects do not? Furthermore, are these ambiguous "qualities of similarity" ineffable or relative? Will two objects always be equally similar, or is this relationship dynamic? While these questions are by no means unaddressed, we pose them here to highlight some fundamental issues in the study of object recognition and introduce some of the broad goals of the present study.

Of fundamental concern to the study of object recognition is the nature of structural representations. A wealth of object information, necessary for identification, is available in an object's structural details. In fact, structural similarity has been shown to be a key determinant of successful retrieval of object information (Arguin, Bub, & Dudek, 1996; Bukach, Bub, Masson, & Lindsay, 2004; Dixon, Bub, & Arguin, 1997). However, structural similarity is a poorly defined concept. Numerous accounts of similarity have been posited, and a brief overview of the extant literature will be discussed before a new series of studies is considered. As our research is primarily concerned with vision, we will mostly limit our discussion to the visual correlates of similarity; however, we acknowledge that similarity is by no means wholly accounted for by the visual qualities of an object. We begin our general discussion with a dialogue on existing methods of measuring visual similarity.

Measures of Visual Similarity

Holistic Accounts

Many studies of visual similarity are based on patterns of difficulty observed in patients with *Category-Specific Visual Agnosia* (CSVA). Individuals who have sustained a brain insult resulting in CSVA retain the ability to parse simple geometric figures from images presented to the retina, but are generally unable identify objects from a specific category. Often times CSVA patients exhibit difficulty with biological or natural objects (Bukach et al., 2004). Humphreys & Forde (2001) suggest that the greater visual similarity of biological objects is an important factor in understanding the deficits associated with CSVA (though there may be others). Thus, CSVA can be thought of as resulting from a brain insult that affects an individual's ability to discriminate highly similar objects; however, as mentioned above, the concept of similarity requires some clarification.

One way of thinking about structural similarity is in terms of holistic object representations. For instance, a high degree of contour overlap (analogous to overlaying two photograph negatives) and the sharing of gross feature (e.g., arms, legs, eyes) may drive similarity judgments (Humphreys, Riddoch, & Quinlan, 1988). In an attempt to explain the deficits observed in patients with CSVA for biological objects, Humphreys et al. had normal observers rate the structural similarity of exemplars from several biological and non-biological categories. They found that observers rated the biological categories as more structurally similar. Participants also reported that exemplars in the biological categories shared more common features. Furthermore, Humphreys et al. compared line drawings (Snodgrass & Vanderwart, 1980) by parceling off the images into a grid and comparing the degree to which the lines within each window of the grid overlapped and found that objects from biological categories show a higher degree of "contour overlap." Thus, contour overlap is posited as a model for predicting perceived object similarity.

The findings of Humphreys et al. (1988) provide evidence that holistic measures of similarity can predict the difficulty of normal observers to name and discriminate objects and can at least partially account for the category-specific deficits seen in patients with CSVA. However, the methods by which contour overlap is assessed may be questionable. Using a pixel-by-pixel method of assessing holistic similarity (where corresponding pixels are either both black, both white or mismatched) as opposed to the grid-method employed by Humphreys et al., it has been shown that line drawings of artefactual objects (e.g., tools and clothing) actually show a higher degree of holistic similarity than biological objects (Laws, Gale, Frank, & Davey, 2002). These findings are in direct opposition to those of Humphreys et al. (1988), and draw into question the usefulness of assessing visual similarity in terms of these holistic measures. However, there is evidence that some objects (namely faces; e.g., Farah, 1992; Tanaka & Farah, 1993) are processed holistically and even some modern, part-based computational models of object recognition now include layers for addressing objects holistically, but see below.

Proximity Accounts

Other measures have been proposed to account for object similarity that de-emphasize the importance of holistic object measures in favor of a model whereby similarity can be accounted for by inter-object distance in a multidimensional space where axes represent structural dimensions of an object (e.g., length and width; Kruschke, 1992). That is, when graphed according to their perceived values on individual structural dimensions, the distance between two object nodes in a multidimensional space will determine similarity, with similarity inversely proportional to inter-object distance (see Figure 1). However, inter-object distance can be calculated in one of two ways, and the most appropriate method is the subject of some debate. For instance, Euclidean distance is calculated by measuring the shortest distance between any two points. Along a single dimension this is accomplished by calculating a simple change in magnitude; however, when multiple dimensions are considered the Pythagorean theorem is used to calculate Euclidean distance. The other common metric for calculating proximity is a city-block measure of inter-object distance. City-block distances can be thought of as a summation of the distance along each separable dimension. For example, in a simple, two-dimensional space, any two points (i.e., objects) in the space can form a right triangle if a line is drawn between the points and two additional lines are drawn parallel to the axes (see Figure 1). In this situation, the Euclidean distance between the points is represented as the hypotenuse of the triangle, whereas the city-block distance is represented by the sum of the two legs of the triangle.

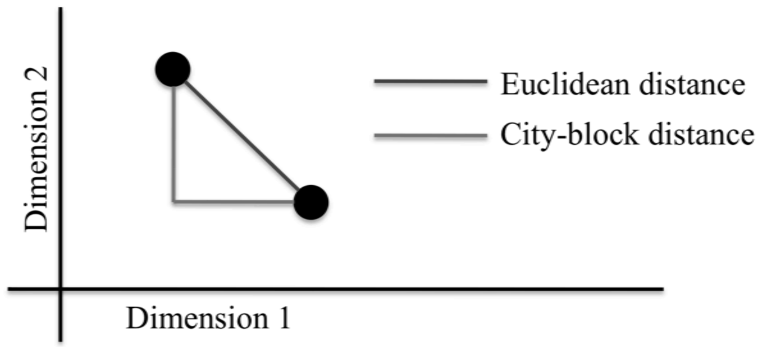

Figure 1. A representation of how Euclidean and city-block metrics of object proximity differ. In the figure the black dots denote 2 unique objects represented in a two-dimensional space. Euclidean distance is represented by the hypotenuse of the super-imposed triangle (black line), whereas city-block distance is represented by the sum of the two legs of the triangle (grey lines). In both accounts, similarity increases as proximity increases.

The appropriateness of these two metrics has been discussed. While some models apply a city-block metric for assessing proximity (Kruschke, 1992), other accounts argue that a Euclidean metric may be more appropriate (Dunn, 1983). The most appropriate metric seems to be highly dependent on the attributes of the assessed dimensions. That is, while models similar to Kruske's model (1992) use a city-block metric to calculate inter-object distance, Dunn posited that when objects can be represented in an *isotropic* space (a space in which the units for every dimension are directly comparable; e.g., millimeters and centimeters) similarity is best accounted for by a Euclidean metric. Alternatively, when objects must be represented in a *metaphorical* space (a space in which the units for every dimension are not directly comparable. e.g., millimeters and degrees of tilt) similarity is best accounted for by a city-block metric (Dunn, 1983).

What is important to note about both models is that proximity is not treated as an absolute, physical measurement, but rather as a perceived value determined by Gaussian functions and heavily influenced by attention. Thus, psychological proximity is not in and of itself a singular attribute of an object but rather a composite of a number of influencing factors including attention and perhaps other object attributes such as shared features (see next section). This distinction between psychological proximity and structural/physical proximity will be discussed further and is paramount to our study and the interpretation of its results.

Shared Features Accounts

It is likely that the psychological proximity metric utilized by Kruschke (1992) and Dunn (1983, among others) may include the interpretation of shared object features. Goldstone explains the relationship between object features and object dimensions such that "a feature is a unitary stimulus element, whereas a dimension is a set of linearly ordered features" (R. L. Goldstone, 1998, pg. 588). Thus, while 1.5 centimeters and purple can be thought of as features, the corresponding dimensions of these features would be length and color, respectively. It has been argued that shared features will have an effect on object similarity when one considers objects as distributed across a multidimensional space. That is in addition to attentional effects, shared features may be a factor influencing the interpretation of similarity (i.e., psychological proximity). Figure 2 illustrates how structural proximity alone cannot account for perceived similarity and how judgments of similarity may be influenced by shared features (see *Integration of*

Distributed Representations and *Distributed Feature Networks* below for a more detailed explanation of this effect). In sum, objects with a large number of shared diagnostic dimensional values (i.e., features) will be more similar than those with less. Support for this shared features component of object similarity comes from numerous studies of a CSVA patient (ELM) as well as normal observers (Arguin et al., 1996; Bukach et al., 2004; Dixon et al., 1997).

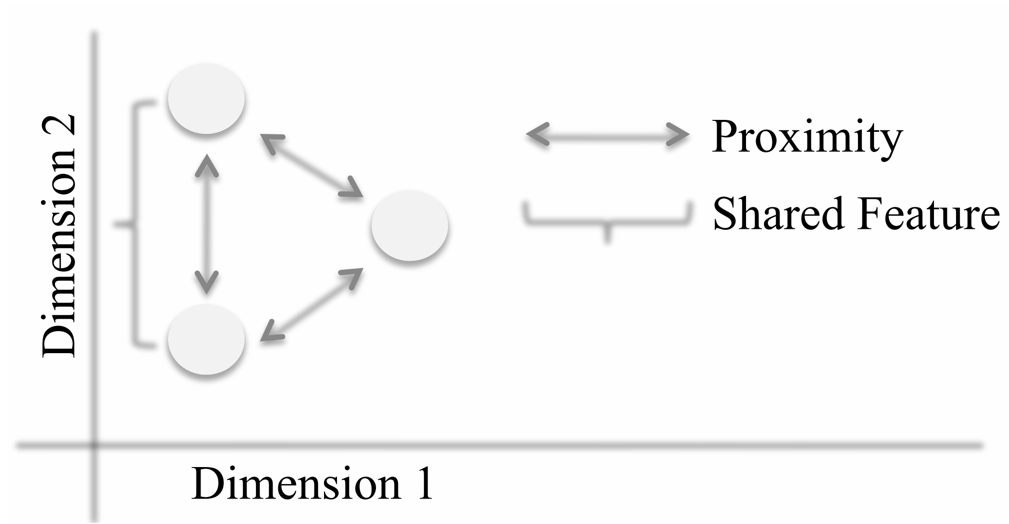

Figure 2. Explanation of two ways in which a multidimensional model of object recognition can account for object similarity. The circles denote three unique objects represented in a two-dimensional space. Structural inter-object proximity is indicated by arrows and shared features are indicated by brackets. Note that if structural proximity alone is considered all three objects should be perceived as equally similar; however, the sharing of a feature on Dimension 1 by two of the objects should increase their perceived similarity to one another relative to the third.

Psychological Distance and Pairwise Comparisons

It is important at this point to stress two fundamental features of the measures of visual similarity discussed so far. First, with the exception of the holistic methods, all of the models discussed so far depend on measures of perceived similarity (i.e., psychological as opposed to physical object comparisons). In Kruschke's model, distance is not determined by calculating the physical distance between stimulus features as one might do with a ruler, but instead tracks perceived distances in psychological space. The distinction is subtle but paramount to our research aims. It may be that psychological distance (typically determined by performance on pairwise comparison tasks; see Arguin & Saumier, 2000 for an example) confounds all of the factors that contribute to structural similarity (e.g., physical proximity and the sharing of features, among others). That is, many factors should contribute to this psychological proximity, including the sharing of features and set characteristics as well as physical proximity. Performance outcomes measure the end product of all such computations, and thus combine all of the factors that may influence similarity (i.e., the measure already includes the effect of shared features and other psychological variables that may alter simple physical differences between stimuli). To examine the impact of shared features, we therefore relied on physical measures as a baseline. In the experiments recounted below we tried to isolate the factors of perceived similarity, and so controlled for physical proximity of objects. While access to concrete structural feature information (e.g., 3 cm, etc) may or may not be available to the perceptual system we isolate it as a factor here not to suggest that it cognitively relevant but merely to better understand the influence of other, non-distance relevant factors of similarity such as shared features and object set properties.

The next important distinction to make is that all of the measures of similarity discussed thus far rely on pairwise comparisons of objects. That is similarity is commonly treated as a property of any two objects and many studies norm similarity of objects by participants' judgments of pairwise similarity (Arguin and Saumier, 2000). It is far more likely, however, that the characteristics of an entire object set will influence perceived similarity, such that changing the characteristics of the set will influence setwise confusions. Take for instance shared features accounts of similarity (discussed above), while any two objects may share features that may influence pairwise judgments of similarity (see Figure 2) certain features may be shared by multiple objects within a set. In this way, the sharing of features is less a pairwise characteristic than a setwise characteristic. Simply, shared features influence judgments of similarity, than pairwise comparisons should not be a sufficient metric for assessing similarity.

This brief overview of methods employed to gauge similarity demonstrates how the seemingly simple concept of visual similarity is far more complex than one might assume. Moreover, a discussion of methods for measuring similarity begs another question: How is object knowledge represented in the brain? This question is integral to understanding object similarity and each of the above methods makes certain assumptions about the nature of object representations. Therefore, we will now discuss how object representations have been modeled and the impact of these models on different methods for measuring object similarity.

Assumptions: Object Representations

Of primary concern to understanding object recognition is whether objects are represented as holistic figures or as a series of distributed component features. Accounts of object similarity like those posited by Humphreys and colleagues (Humphreys et al., 1988; Humphreys & Forde, 2001) assume that objects are represented as a whole. In contrast, multidimensional accounts of object similarity that consider object properties such as perceived size (Dunn, 1983; Kruschke, 1992) and shared features (Arguin et al., 1996; Bukach et al., 2004; Dixon et al., 1997) assume that component features of an object are represented in a distributed fashion during encoding and must be integrated during retrieval. Support for each model of object representations will be discussed in turn.

Holistic Models

Some older computational models have demonstrated systems in which a single node may represent one entire object. For instance, Grossberg's *Adaptive Resonance Theory* (ART) model demonstrates that a single unitary representation of an object (e.g., a word) will respond to a series of perceptual features at an earlier level of the model. As the relationship between these earlier perceptual features and the later unitary representation is bidirectional, activation of the single object unit will in turn activate the entire pattern of correlated perceptual features (Grossberg, 1984). In this way, certain objects may indeed trigger a unitary holistic representation, providing support for holistic measures of similarity (Humphreys et al., 1988; Humphreys & Forde, 2001). However, Grossberg utilized word stimuli for his model. As common or frequent words often represent over-learned stimuli composed of smaller component features (letters) it is possible that holistic representations result from commonly activated (i.e., learned) patterns of features (see *unitization* below).

More recent models of object recognition, such as Edelman and Intrator's *Chorus of Fragments* (CoF) model (2003a; 2003b) assess the degree to which images presented to the retina fit with an alphabet of *what* + *where* cells. That is what + where cells assess different portions of the image presented to the retina by measuring the goodness of fit of a number of *object fragments* with that portion of the object. In this way, there is no need to break an object down into its component parts – an object can simply be dealt with holistically. Indeed, Edelman and Intrator argue that while the process by which objects could be parceled into component features is computationally easy, biologically it is too complicated to be viable. However, this topic has been much debated in the literature, and while an in depth recounting of the argument is beyond the scope of this paper, there is voluminous evidence to support a distributed features model of object recognition, some of which is discussed below (see Barsalou, 1982; Dunn, 1983; Treisman & Gelade, 1980; Biederman, 1987; Hummel & Biederman, 1992; Kruschke, 1992; Hummel & Stankiewicz, 1998; Hummel, 2001; and Hummel 2003 for a response to Edelman & Intrator, 2003a).

Integration of Distributed Representations

Prior to discussing computational models that support a distributed model of objects, we must address how objects may be parsed apart and reassembled, to allow for a distributed representation of an object. Implicit to a distributed model of object recognition is the necessity to integrate object features from a dispersed network. This process of integration can be understood in terms of *Feature Integration Theory* (FIT, Treisman & Gelade, 1980). According to FIT, some object features are processed separately and require an additional integration step in order to be linked as a single precept. Feature integration can be modulated by external factors such as task demand and time constraints. Specifically, a high level of attention is necessary for the integration of diagnostic object dimensions when objects in a set share values for those dimensions. For example, in one experiment additional time was needed to find a target that shared diagnostic features with distracters (e.g., a green X in a field of blue Xs and green Ts) in a visual search compared to when distracters all had unique values for the dimensions that were diagnostic to the task (e.g., a red S in a field of blue Xs and green Ts). Conversely, when participants had an insufficient amount of time to attend to all the objects in a display they often recalled objects with feature combinations that were present in the search but never paired. Thus, if a participant was briefly presented with a display of green Xs and blue Ts, they might falsely recall a green T. These confusions are referred to as *illusory conjunctions*. Although typically studied in the context of binding between two feature domains such as color and form, FIT has also been applied to the binding of two features within the domain of structural form. For example, illusory conjunctions have also been demonstrated with letter fragments such that when presented with a display containing only Ps and Qs, participants sometimes reported having seen an R (a combination of the Q's tail with the letter P) (Treisman & Gelade, 1980). However, few studies have examined this phenomenon with objects. Thus, the FIT model of object recognition provides an explanation for why shared features should influence the perception of objects. If features must be integrated to form a situationally relevant and useful percept then objects will be defined by those features that they do not share in common. This sharing of features is particularly relevant when trying to identify an object within a set, as the number of shared features within the object set will partly define that sets similarity. For example, in an object set that contains three letters – P, Q and R – neither the semi-circle component (shared by the R and the P) nor the tail component (shared by the R and the Q) are by themselves diagnostic of a single object. Thus in order to properly identify an R, both the semi-circle component and the tail component must be integrated. Note that, as mentioned above, most of the work pertaining to the integration of distributed representations is based on behavioral data (accuracy and response time) and is therefore based on measures of perceived similarity or distance in a psychological space. The importance of actual physical dimensions (i.e., length, etc) remains underspecified.

Distributed Models

Distributed accounts of object similarity find support from computational models that highlight multidimensional object representations. Kruschke (1992) developed an exemplar-based, connectionist model of distributed diagnostic features that can account for similarity in this way. The *Attention Learning Covering Map* (ALCOVE) treats objects as points in a dynamic, multidimensional space. At the input level, each node represents a perceptual dimension, with features defined by the level of activation at the input node. Interestingly, attention can mediate the relevance of individual input nodes, such that those dimensions most diagnostic across previous learning trials are weighted more strongly in future episodes. Input nodes project forward to the hidden level, where nodes represent points in multidimensional space. Next, hidden nodes project forward to the output level where nodes represent a task-dependent categorization of the object, mediated by learned associations.

Kruschke's model can account for both distributed accounts of similarity discussed already: Similarity as a function of psychological proximity and as a function of shared features. In ALCOVE, *specificity* very nearly approximates (psychological) proximity. Specificity refers to the overall width of the activation profile of a node at the hidden level. Thus, specificity can be thought of as definitive of an exemplar's confusability, insofar as it specifies the precision with which an object feature is mapped in multidimensional space. Furthermore, although not specifically discussed by

Kruschke, ALCOVE can also account for similarity due to shared features in terms of attentional weighting. For instance, in an extreme example, if two exemplars varied on a single diagnostic dimension (i.e., shared all but one feature), and that diagnostic dimension was given no attentional weight (i.e., $\alpha = 0$), the dimension would be totally collapsed in multidimensional space, and therefore the two exemplars would be perceived as identical. In the model, attentional weight is learned from dimensional diagnosticity across multiple trials; however, other factors, namely attentional capacity, would be presumed to affect attention weighting as well. Again however, it must be stressed that ALCOVE is based on perceived object features and does not account for actual physical features of an object.

In addition to ALCOVE, Hummel and colleagues have proposed models of object recognition that treat objects as a collection of features which must be integrated in order for an object to be properly identified (Hummel & Biederman, 1992; Hummel & Stankiewicz, 1996; Hummel & Stankiewicz, 1998; and Hummel, 2001). JIM.3 (The third and most current revision of *Jim and Irv's Model;* Hummel, 2001) is a viewpoint invariant model that identifies the presence shape primitives (geons, see Biederman, 1987 and below) by synchronizing the oscillations (akin to synchronized neural firing) of cells in Level 1 and 2 of the model which respond to orientation (L1), vertices, 2-D axes of symmetry, and oriented, elongated blobs of activity (L2). Interestingly, JIM.3 includes a holistic component in layer 5, a revision from previous incarnations of the model. Further, as mentioned above, models such as JIM.3 which assume the breaking-up of images into components have been attacked on the assumption that such breakdown of objects is neurologically unrealistic (see Edelman & Intrator, 2003a; Hummel, 2003; and

Edelman & Intrator, 2003b for a back-and-forth on the issue). However, the extant literature still seems to support a distributed model of object recognition (Barsalou, 1982; Dunn, 1983; Treisman & Gelade, 1980; Biederman, 1987; Hummel & Biederman, 1992; Kruschke, 1992; Hummel & Stankiewicz, 1998; Hummel, 2001; to name a few) and Hummel (2003) provides a heated defense of distributed models in which he cites his own (JIM.3) and defends distributed representation models against common misconceptions about viability.

Importantly, both holistic models such as Edelman & Intrator's (2003a) and distributed models such as Kruschke's (1992) and Hummel's (2001) have ways of explaining visual similarity. However, holistic models cannot account for shared features accounts of similarity as features do not factor into such models at any point. Therefore, any evidence for the role of shared features on similarity would support a distributed model of object recognition and be inexplicable in terms of holistic models.

Factors Influencing Visual Similarity

Having reviewed some commonly utilized methods for measuring object similarity and the assumptions inherent to these methods, we will now discuss those factors that have been found to specifically influence object similarity. Factors associated with object similarity can be broken down into four domains: Brain organization, object properties, past experiences and task demands. We will discuss each of these domains in turn and provide supporting evidence for each of the factors discussed.

Brain Organization

Distributed Feature Networks. As mentioned above, how object information is represented in the brain will affect perceived visual similarity. If objects can be represented as single nodes (i.e., holistically) as suggested in Grossberg's model (1984), similarity may depend on the total degree of overlap between any two objects (i.e., holistic similarity). However, even Grossberg's model is capable of representing objects as a distributed network of component features, regardless of whether they activate an additional unitary holistic node. Whether object features are stored separately and need to be integrated at retrieval (Treisman & Gelade, 1980) will effect how similarity is conceptualized. For instance, if object features must be integrated at retrieval, object categories with many shared features will require the integration of a large number of features in order to prevent object confusions. In an extreme example, two objects that share all but a single feature will be indistinguishable if the sole diagnostic feature is not integrated. In this way, similarity can be interpreted as the load placed upon an integration mechanism, especially when the featural information available is impoverished. Holistic accounts of object similarity take proximity of all structural dimensions into account, whereas distributed accounts allow for the additional factor of shared features and feature weights. Thus, finding an effect of shared features on object similarity provides indirect evidence for a distributed feature network of object representations.

Through their study of CSVA patient ELM, Arguin, Bub and Dudek show evidence for the effect of shared features on object confusions (Arguin et al., 1996; Dixon et al., 1997). When tested with an auditory-word/picture matching task with line drawings of fruits and vegetables, ELM's primary confusions were made for objects with shared structural features, such as a cucumber and a banana (both are elongated and differ only on curvature). These results suggest a kind of paucity of structural information during feature integration at recall (similar results were not present in tests of perception, but see below). That is, if ELM failed to properly integrate features from a curvature dimension during object recognition, a line drawing of a cucumber would be indistinguishable from that of a banana.

To provide further evidence for ELM's recall confusions when objects shared features, Arguin et al. (1996) created a novel set of stimuli, which could vary along three structural dimensions (elongation, curvature and tapering). On an object set with only a single diagnostic dimension (1D, i.e., not requiring integration of diagnostic features), ELM performed relatively well in a match to location recall task (29% error); however, for an object set with two diagnostic dimensions (2D), ELM performed significantly poorer (56.7% error). Thus, when objects had to be differentiated on the basis of two diagnostic dimensions (with every exemplar sharing one feature with another exemplar) rather than one, ELM performed much poorer. Furthermore, the 1D object set employed by Arguin et al. was far more proximal (inter-object distance was smaller) than in the 2D object set, presumably increasing the similarity of the objects in the 1D set relative to the 2D set (see proximity accounts above). Still, ELM showed most difficulty with the 2D set. Specifically, ELM only confused objects in the 2D set that shared a feature from one of the diagnostic dimensions (i.e., object pairs parallel to a dimensional axis in Figure 3). ELM never confused objects that did not share a structural feature (object pairs diagonal to one of the dimensional axes in Figure 3). Therefore, shared features drove ELM's confusions, a fact that cannot be accounted for by object proximity. Figure 3 depicts the structural relationships between items in the object sets used by Arguin et al.

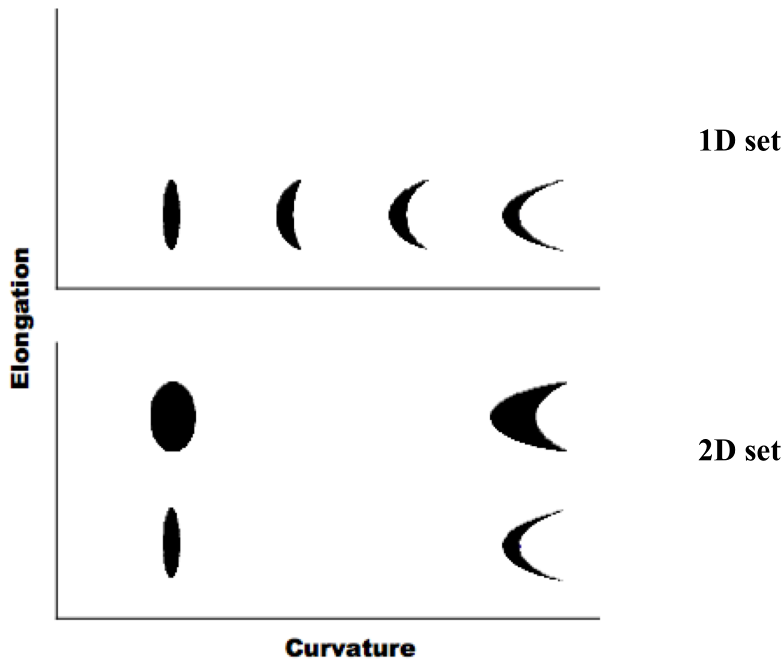

Figure 3. The structural relationship of objects in a 1D and a 2D object set (Arguin et al., 1996).

This study highlights the fact that shared features caused confusions in CSVA patient ELM that could not be accounted for by inter-object proximity. Only a distributed model can account for this effect of shared features over proximity. Further, similar results have been shown in normal observers (Arguin & Saumier, 2000; Blais, Arguin, & Marleau, 2009). Also, in addition to providing evidence for the role of a distributed model of object representations on object similarity, the Arguin et al. (1996) study also provides evidence for the hierarchical nature of object representations and feature integration.

Hierarchical Processes. According to Arguin et al. (1996), there are two points at which integration of structural object features might take place: The encoding stage where a percept is created from visual input and the recall stage where separately stored structural features are retrieved. CSVA patient ELM showed a deficit in discriminating objects with shared features, but only when memory for shape location associations had to be recalled. This deficit was not present in a perceptually demanding match to sample task (note that even a match to sample task requires a small reliance on working memory). Thus, for ELM, integration of structural features seems to be impaired only during a recall stage and not during an encoding stage.

However, integration of structural features during perception has also been shown (Arguin & Saumier, 2000; Blais et al., 2009). Using a set of stimuli that varied along the structural dimensions of tapering, elongation and curvature, similar to those used in studies with CSVA patient ELM (Arguin et al., 1996), Arguin and Saumier (2000) devised a task to assess whether structural features of an object must be integrated during perception, similar to the procedure used to test FIT (Treisman & Gelade, 1980). During a visual search participants were asked to distinguish a target from a varying number of distracters. In one condition, targets possessed unique values on the two structural dimensions of interest and did not share any features with the distracters (No-Conjunction). In the No-Conjunction condition, integration of features was not necessary to identify the target. That is, since the target possessed unique values on the structural dimensions of interest for the task, attention to a single dimension was sufficient. In another condition, targets shared one of two features with each of the distracters, thus, requiring the integration of both features in order to identify the target (Conjunction condition). The structural composition of the No-Conjunction and Conjunction object sets is depicted in Figure 4.

Arguin and Saumier reasoned that if the objects in their two conditions could be identified holistically, no behavioral differences would exist between the No-Conjunction and Conjunction conditions. However, search rates were significantly longer in Conjunction condition than in No-Conjunction condition. The extra time needed to perform the task for Conjunction object sets is interpreted by the authors as reflecting the time required to integrate structural features during perception.

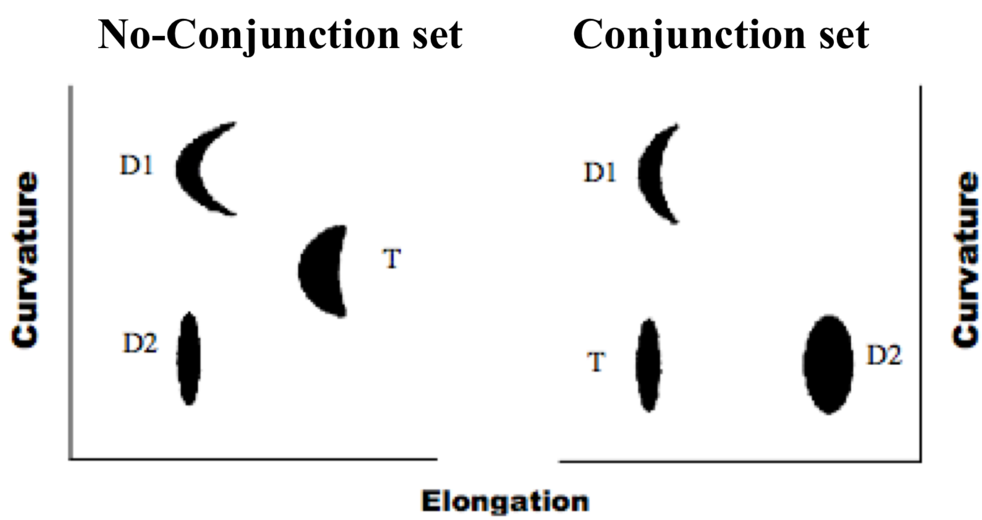

Figure 4. An example of the stimuli utilized in visual search paradigm showing the structural relationship between targets (T) and distracters (D) for the No-Conjunction and Conjunction object sets. In this example, the target in the No-Conjunction object set possess unique values on the curvature and elongation dimensions, while the target in the Conjunction set possesses no unique dimensional values (Arguin & Saumier, 2000).

These two studies demonstrate that integration must take place during perception and also during recall. Further, these processes may be dissociable, as ELM did not show difficulty in a perceptual task. As such, this hierarchy of multiple integration processes may affect visual similarity depending on the nature of the task. For instance, it is possible that the similarity between two objects may be perceived differently during encoding and during retrieval.

Feedback from higher levels of processing. Some evidence suggests that perceived structural similarity is modulated by feedback from higher levels of processing. For instance, studies of ELM have demonstrated that conceptual information modulates structural confusions such that ELM did not make object confusions when objects were distinctive conceptually (Dixon et al., 1997). Further, the results of a study of normal observers indicate a similar effect of conceptual similarity modulating structural similarity (Bukach et al., 2004). These studies provide evidence that suggests that information from higher levels of object processing (e.g., conceptual information) may feedback to lower levels of processing (i.e., structural information) to help resolve confusions. Thus, while this study will primarily focus on the effect of structural features on visual similarity, it must be acknowledged that even structural similarity may be modulated by information outside of visual processing (See also, Kinka, D., Roberts, K., and Bukach, C. M. in preperation).

Dynamic nature of object representations. In some capacity, the dynamic nature of object representations has already been alluded to. For example, both ALCOVE (Kruschke, 1992) and FIT (Treisman & Gelade, 1980) emphasize a central role of selective attention to diagnostic dimensions. These models can be contrasted with a fixed architecture model of object recognition such as Biederman's *Recognition-by-Components* (RBC) model (1987). According to this model objects are represented as the combination of a limited number of shape primitives called geons. These geons, composed of the lowest level structural information received through the visual modality (e.g., edges and vertices), are conjoined during perception until they represent an integrated object structure. This model suggests that, although attention to structural features may vary, all object features are encoded and integrated during perception. That is, the Recognition-by-Components model assumes that structural features are a fixed and invariable part of object representations. Models such as Beiderman's original RBC model do not address the significance of integration of stored features and leave recognition processes underspecified. Thus, unlike dynamic models of object representations, fixed architecture models do not account for any episodic component of object knowledge. The absence of this episodic component weakens fixed architecture accounts of object representations[1].

Unlike fixed architecture models, dynamic models allow for only a subset of an object's structural features to be activated during retrieval. In this case, diagnostic features will depend on the nature of the task. Furthermore, history will impact the features that have been integrated together before, and therefore be "reactivated" together again because of their correlational nature. Past history will also impact saliency of features. This account of dynamic models is similar to that posited by Kruschke's ALOVE model (1992) and also Barsalou's (1982) idea of flexibility in conceptual representations. According to Barsalou, the representation of an object at any given time is not a stable entity, but rather contingent upon situational constraints such as goals and past experience. Further, similar to ALCOVE and FIT, Barsalou contends that selective attention to certain object features influences not only which features are encoded but

[1] Modern computational models which utilize geons (Hummel & Stankiewicz, 1998; and Hummel, 2001) can now account for attentional effects in terms of the degree to which neural firing between the first couple layers of the model is synchronized and are thus far less rigid than Biederman's original RBC model. In fact, as mentioned above, JIM.3 even includes a holistic component. However, as JIM.3 still relies heavily on the identification of formerly identified geons from a limited alphabet, its treatment of non-geon or unspecified shape primitives is relatively underspecified.

also which perceptual cues will be most salient for future retrieval of object information. Thus, in a dynamic model object representations (and thus object similarity) is very much influenced by selective attention, which will be situationally and environmentally dependent.

Object Properties

In addition to brain organization, similarity will also be dependent upon the properties of the object categories being considered, such as inter-object proximity and shared features. As discussed above inter-object proximity (whether measured using a Euclidean or city-block metric) will affect object similarity such that as distance increases similarity decreases (Dunn, 1983; Kruschke, 1992). Further, shared features will affect object similarity such that an increased number of shared features will increase inter-object similarity, especially when there is an impoverished representation of object features (see above).

Past Experience

Past experiences will likely affect object similarity as well. One way in which this might be understood is through the study of a phenomenon similar to integration known as *unitization*. According to Goldstone, unitization involves the combination of multiple, co-occurring features to form a new, singular, functional unit. This perceptual learning effect is assumed to take place when the configuration of a stimulus is complex and requires attention to multiple, co-occurring features (R. L. Goldstone, 1998). For instance, evidence for unitization has been found in a visual search paradigm designed to assess rates of perceptual learning (Czerwinski, Lightfoot, & Shiffrin, 1992). The stimuli utilized by Czerwinski et al. were composed of separated line segments that were diagnostic to the object; however, objects shared features (line segments) so that no one line-segment was by itself sufficient to identify a particular stimulus. Participants displayed a gradual reduction in response time over multiple days of training, which the authors attribute to “chunking” of the line-segment features so as to create a single functional unit of the stimulus. Therefore, rather than attending to at least two features individually to perform the task, participants could attend to a pair of highly rehearsed or “chunked” features, thus decreasing response time. Similar results were later found, providing evidence for the unitization of as many as five individual features in a novel stimulus set (R. L. Goldstone, 2000).

Unitization is likely to occur when co-occurrence of object features is high between exemplars in a set, and suggests a similar response. On the other hand, if two features represent independent sources of variation between two objects, those features will likely be processed in turn (see R. L. Goldstone, 1998 for a discussion). Thus, unitization must be learned over a number of individual experiences with a set of stimuli (Also see the discussion of Barsalou’s theory above). This provides an example of how past experience may modulate perceived similarity. If multiple object features become unitized across a number of learning episodes, the “chunk” of unitized features is likely to be processed more holistically in the future. The impact of this chunking on similarity is not well understood. One might hypothesize; however, that that with practice resulting in unitization errors driven by shared features would be less likely because all of the relevant dimensions would be activated and integrated, and thus the impact of shared features could be attenuated.

Task Demands

Lastly, similarity should be dependent upon task demands. One example of evidence for a task-relevant account of object perception comes from work by Feldman and Richards, who found that rectangles could be characterized on the basis of either length and width dimensions or area and shape dimensions, depending on the nature of the task (Feldman & Richards, 1998).

Similarly, Schyns and Rodet used objects they refer to as Martian cells, to show that features used to identify an object are dependent on learning condition and the diagnosticity of structural features (Schyns & Rodet, 1997). That is, through subtle manipulation of their stimuli, the authors demonstrate that, depending on the learning condition, participants categorized the same objects either by component parts (e.g., x and y separately) or by a synthesized part (e.g., synthesized xy component). In addition to demonstrating that a fixed-feature model fails to acknowledge the modulatory role of categorization history and diagnosticity of task-dependent structural features (see Schyns, Goldstone, & Thibaut, 1998 for a review), Schyns and Rodet provide further evidence that task demand influences those features attended to. As such, models of similarity based upon comparison of features must account for the fact that task demand largely influences those features that will be attended. Indeed, the similarity of two objects may vary depending upon which features are attended and compared.

Current Study

The current study seeks to assess the role of shared structural features on visual similarity while controlling for any effect of inter-object distance. In so doing we hope to demonstrate that the *psychological space* in which objects are represented in the brain is best represented by a dynamic model. Specifically, we will show that a model that only accounts for structural object features (i.e., structural proximity) in a *physical space* is not by itself sufficient in predicting participant confusions. The previous studies all refer to psychological space – the end product of all the factors that influence the perceptual process. We intend to pull apart some of these factors. To do this we will define proximity in terms of physical space to see how proximity and shared features between objects impact perceptual confusability. The first study assess the effect of shared features on object similarity in three different tasks (Experiments 1a, 1b, and 1c) which task perception and memory to different degrees. The second study (Experiment 2) assesses the time course of structural feature integration in perception by utilizing electrophysiological techniques.

To test the effect of shared features on normal visual processing a novel set of stimuli has been created that can be manipulated on the basis of two diagnostic structural dimensions. As the structural dimensions of tapering and pinching are similar to those used in studies of ELM (Arguin et al., 1996; Dixon et al., 1997), we utilized these dimensions in creating our stimuli (Figure 5).

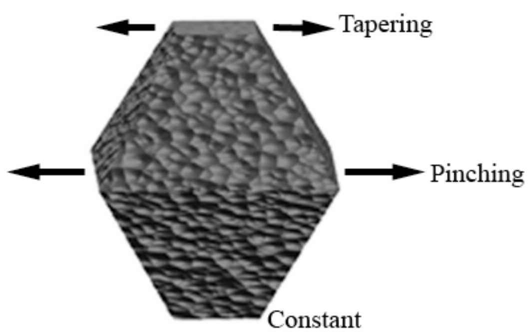

Figure 5. An example of how structural dimensions are manipulated between stimuli. The horizontal length of the top of the object is referred to as tapering and the horizontal length of the central part of the object is referred to as pinching. The length of the base of the object is constant.

Further, to control for proximity two object sets are utilized that vary only on their total number of shared features. The two object sets are mapped in a two-dimensional space defined by values of tapering and pinching (see Figure 6). The first object set forms a square configuration when plotted against the tapering and pinching values of the set. Likewise, the second object set forms a diamond configuration. The two object sets (henceforth referred to as square and diamond) each contain eight novel objects. While the square object set contains 14 object pairs that share a feature on a single dimension (e.g., objects a and b) the diamond object set contains only 6 such pairs.

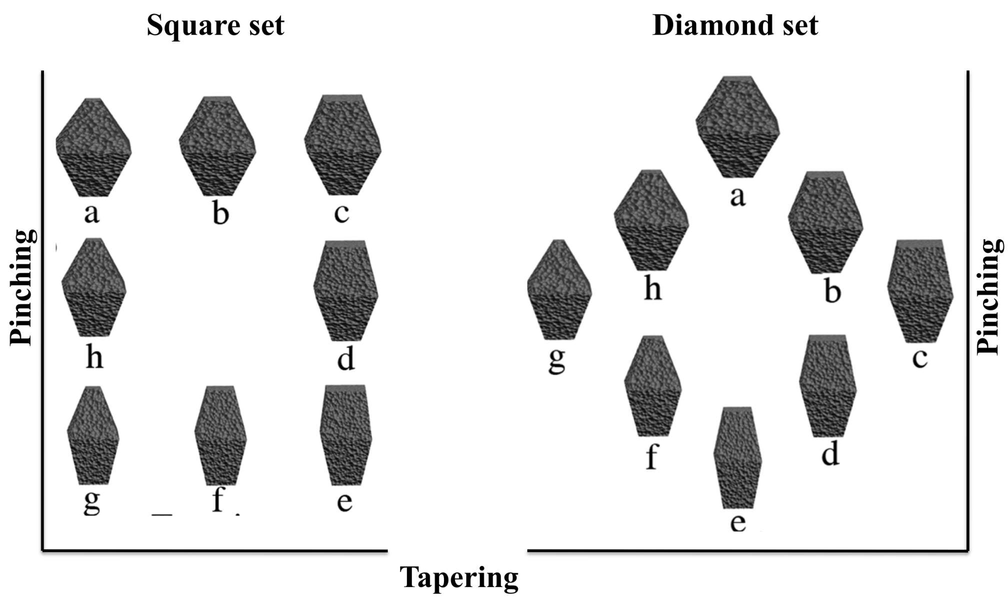

Figure 6. Stimuli from the square and diamond object sets graphed according to values of tapering and pinching. Proximity is controlled for between the two object sets, such that objects a and b in both the square and diamond set are equidistant in terms of Euclidean distance. The square object set contains more shared features (e.g., objects a and b in the square object set share a value on the pinching dimension, whereas objects a and b in the diamond object set do not) relative to the diamond object set.

In each object set, those exemplars that share a feature form a line parallel to one of the two axes. This sharing of features can be referred to as a *parallel relationship,* further qualified by the non-shared dimension. Thus, a parallel-tapering relationship would consist of two objects (parallel to the tapering axis) that vary along the tapering dimension only, and share a value on the pinching dimension (e.g., objects a and b in the square set and objects h and b in the diamond set, see Figure 6). In contrast, objects with unique values for both tapering and pinching (i.e., no shared features) create a diagonal and are said to have a *diagonal relationship*. Of the 14 object pairs with shared features in the square condition and the 6 such pairs in the diamond condition, half exhibit parallel-tapering relationships and the other half, parallel-pinching relationships.

Other than number of shared features, the two object sets are equivalent in physical appearance, with uniform low-level visual properties. Further, the average physical inter-object distance of each object set is identical, controlling for any effect of physical proximity. This is accomplished by controlling for the pair-wise Euclidean distances of objects within sets (i.e., objects a and b in the square condition and objects a and b in the diamond condition are equidistant in physical space). In a sense, the diamond object can be conceptualized as the square object set rotated 45 degrees in a tapering x pinching space. Because the space created by tapering and pinching dimensions is isotropic, the Euclidean metric of distance is used to equate distance in our stimuli (Dunn, 1983).

Unlike Arguin and Saumier (2000), who had participants make pairwise judgments about object similarities to norm their stimuli, we have chosen to norm our stimuli according to actual distance in physical space. This decision is motivated by a desire to not only maximize homogeneity of objects within a set (thus, increasing the likelihood of object confusions in normal observers), but also to allow distinctions between confusions driven by (structural) proximity and those driven by shared features.

By allowing their stimuli to be normed based upon the similarity judgments of participants, Arguin and Saumier have confounded (at least) two components believed to influence structural similarity – participants' judgments of similarity will be a determined by a combination of these two components of psychological space and thus reduce the power of the researchers to detect differences based upon shared features alone. Thus, having controlled for physical proximity and other anticipated confounds, any difference in perception between the square and diamond condition is assumed to be attributable to their differing number of shared features.

EXPERIMENT I

Introduction

Shared object features have been shown to impact object similarity (Arguin, Bub, & Dudek, 1996; Arguin & Saumier, 2000; Blais, Arguin, & Marleau, 2009; C. M. Bukach, Bub, Masson, & Lindsay, 2004). Arguin et al. (1996) posit that this effect is understood through the amount of strain placed on an integration mechanism. Thus, the more diagnostic features shared within an object set the more features will need to be integrated in order to disambiguate them. In this way, each additional shared feature present within an object set will serve to increase similarity between those objects in the set and as a result increase their confusability. Furthermore, Arguin et al. suggest that there are two points at which integration of structural object features might take place: The encoding stage where a percept is created from visual input and the recall stage where separately stored structural features are retrieved. However, the effect of shared features on object similarity during perception as opposed to during recall is poorly understood.

Part 1 of the current study explores the impact of shared features on visual similarity across different task demands. Three individual experiments investigate this effect. Some evidence for the effect of shared features at perception, in working memory and in long-term memory is available in the extant literature; however, no single study has directly compared this effect across these three domains.

Shared Features in Perception

In a visual search paradigm described above, Arguin and Saumier (2000), found evidence for an effect of shared features during perception. In one condition, targets possessed unique values on the two structural dimensions of interest and did not share any features with the distracters (No-Conjunction). In the No-Conjunction condition, integration of features was not necessary to identify the target. That is, since the target possessed unique values on the structural dimensions of interest for the task, attention to a single dimension was sufficient. In another condition, targets shared one of two features with each of the distracters, thus, requiring the integration of both features in order to identify the target (Conjunction condition, see Figure 4). Search rates were significantly longer in the Conjunction condition than in the No-Conjunction condition. The extra time needed to perform the task for Conjunction object sets was interpreted by the authors as reflecting the time required to integrate structural features during perception.

Interestingly however, the authors controlled for inter-object proximity in this study by asking participants to make pair-wise judgments of the similarity between objects. That is, proximity was controlled for in terms of a psychological space and not in terms of actual distance in physical space. Thus, Arguin and Saumier did not have the power to properly disambiguate the effect of physical proximity and shared features on similarity separately. One might expect to find a similar effect of integration in an experiment that controls for these two features of similarity.

Shared Features in Working Memory

The role of shared features in working memory has also been demonstrated. Using Chinese symbols Mate and Baqués (2009) tested participants on an old new paradigm, where a set of Chinese characters was studied (encoding stage) and had to be held on-line in working memory. After a 900 ms delay, participants were asked to identify a single previously presented (old) stimuli in a set of new stimuli (retrieval stage). Results indicate that greater object similarity (determined by number, position and shape of strokes that made up an individual symbol) at encoding increased memory performance during retrieval, especially when the answer choices presented during retrieval were dissimilar. But again inter object proximity is not controlled for or even accounted for in this experiment. Further, while this study does not directly assess the effect of shared features on object similarity (object dimensions were not manipulated), it shows how similarity may be addressed in a working memory task. The authors contrast similarity during encoding and retrieval; however, a similar study might address the effect of shared features on similarity in a more carefully controlled paradigm. For instance Arguin et al. (1996) tested ELM for location memory in a working memory paradigm described above. When tested with 1D and 2D objects ELM only confused objects in the 2D set that shared a feature from one of the diagnostic dimensions. ELM never confused objects that did not share a structural feature (see Figure 3). This study supports the role of shared features in similarity perceptions during a working memory task, but the relative effect of shared features on similarity during working memory is still unknown.

Shared features in Long-Term Recall

Lastly, the effects of shared features on similarity during long-term recall have been shown with normal observers (C. M. Bukach, 2004) and with CSVA patient ELM (Arguin et al., 1996; Dixon, Bub, & Arguin, 1997). Indeed, the category specific deficits of ELM (who had properly encoded the structural components of commonly occurring visual stimuli prior to a head injury) at recall are explained in terms of the inability to integrate a sufficient number of diagnostic features necessary to disambiguate two structurally similar objects (see above). By controlling for shared features and physical proximity, it would also be possible to gauge the relative effect of shared features on similarity in a long-term recall task.

The above referenced studies provide a limited but representative sampling of the available data on the effect of shared features on visual similarity. In order to build off of the findings mentioned above while providing a controlled study of the effect of shared features on visual similarity across varying task demands we conducted the three experiments in Part 1. Each of the three experiments will be presented and discussed in turn before a general discussion of our findings is presented.

Experiment 1a

As introduced above, our stimuli control for any perceptual differences that could be due to simple inter-object distance in physical space. As a result, our experiment is designed to detect the effect of any other variables that may influence the composition of a psychological space – specifically the sharing of features. Thus, if shared features impact confusability above and beyond what can be accounted for by proximity alone, this effect will be observed as an accuracy difference between our two experimental conditions. Because the square object set contains more shared features than the diamond object set (see stimulus description above), we predicted that it would show more errors of confusability.

We used a match to sample design that required the participant to discriminate a single target object from the entire set of eight objects. By minimizing working memory load and forcing an 8-alternative forced choice at test, we attempt to maximize perceptual effort while minimizing any potential memory demands. In this way, a performance difference between the square object set group and the diamond object set group in this experiment would be interpreted as a predominant effect of shared features during perception. Such a finding would support the account of shared features at perception posited by Arguin and Saumier (2000). Although there is evidence to support the need for normal observers to integrate object features at both perception and recall, the pattern of performance from patient ELM suggests that integration during recall may be dissociable (Arguin et al., 1996). In this task, we manipulate the number of exemplars that share features during perception and examine evidence for failures of integration by comparing accuracy for object sets that share more vs. fewer features. If shared features cause objects to be more confusable during perception, participants should be less accurate for the square object set than the diamond object set. Further, by conducting a linear regression analysis on participant errors we expect to find that shared features is a significant predictor of participant error. However, we acknowledge that physical proximity will most likely be the stronger predictor of error (justifying our controlling of this factor).

Method

Participants. 16 volunteers recruited from the University of Richmond participated in Experiment 1. Participants ranged in age from 18 to 22 and possessed either normal or corrected vision. Each participant was compensated with either course credit (2 credits/hour) or with cash ($10/hour) for his or her participation. The University of Richmond's Institutional Review Board (IRB) approved this and each of the following experiments prior to there onset, and participants were always treated in accordance with the ethical standards of the APA.

Materials. Two sets of eight gray-scale, 3D objects rendered using Carrara 5 pro (Figure 6), were used in Experiment 1. Importantly, the square object set contains more parallel relationships (i.e., shared features) than the diamond object set.

Design and Procedure. A match to sample design was utilized such that participants had to match a single object to a set of eight, maximizing perceptual effort while placing a minimal demand on memory. Object set was treated as a between-subjects factor. During the experiment, participants were first presented with a fixation cross for 500 milliseconds followed by a target stimulus from the square or diamond object set depending on the participants assignment. The target stimulus was viewable for 2000 milliseconds after which a mask was shown for 500 milliseconds to clear the image on the retina. Following the presentation of the mask, all eight objects from the assigned object set appeared on the screen corresponding to the 8 outer blocks of a 3x3 grid. The locations were numbered in a fashion that corresponded to a keyboard number pad, omitting the number 5. The participant was given an unlimited amount of time to identify the target stimulus using the number pad on a standard Macintosh keyboard. Assignment of objects to location at test was random and target location at test was counterbalanced across trials. Each participant completed four blocks of 64 trials. The experiment was blocked by object set and texture. However, object set was treated as a between-subjects factor in the following analyses to control for generalization of object learning between the sets, therefore only the first two blocks (both with the square object set or the diamond object set) were considered. The first two blocks (one utilizing objects with the crater texture and the other objects with the gravel texture) were counterbalanced by participant. Data from the two object sets were collapsed across the two textures for analysis[2]. The experiment was run on a Macintosh computer using Superlab 4 software.

Results

Accuracy. An independent samples *t*-test was conducted to evaluate the effect of shared features on object perception, as measured by response accuracy. The *t*-test indicates that, any difference between the square (M = 0.71, SD = 0.13) and diamond (M = 0.66, SD = 0.11) object sets failed to reach significance; $t(14) = -0.83$, $p = 0.42$.

Regression. Although the independent samples *t*-test indicates no significant difference between the two object conditions, a multiple regression analysis was conducted to examine the pattern of participant errors to see if the distribution of pairwise confusions could be accounted for by either physical space (proximity), presence of a shared feature (shared features, dummy coded as 1 = a shared feature and 2 = no shared features), and/or the interaction of the two variables[3]. As this regression is primarily exploratory in its objectives and the importance of each predictor is unknown, a forward, step-wise regression method is utilized. The results of this analysis are presented in Table 1. The Durbin-Watson statistic[4] for the model is equal to 2.13, suggesting an acceptable

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[2] As no effect was found for texture nor was an effect found for interaction with texture, data was collapsed across this variable.

[3] Because proximity and dimensionality are calculated between object pairs (i.e., not dependent on object set – square or diamond), data from the square and diamond object set are combined in this and the following regression analyses.

[4] The Durbin Watson statistic is a measure of the correlation between adjacent residuals. The statistic ranges from 0 to 4, with a value of 2 indicating that the residuals are

amount of correlation amongst residuals. The only significant predictor in this model was proximity, which accounted for 56% of the variance.

Table 1. Summary of the forward, step-wise regression analysis in which the pairwise confusion data of Experiment 1a was regressed onto proximity, shared features (coded as 1 = a shared feature and 2 = no shared features) and their interaction.

		Model statistics				Standardized Coefficient Statistics		
		F	*p*	R^2	Durbin-Watson	*β*	*t*	*p*
Model 1		137.80	< .001	0.56	2.07			
	Proximity					-.75	-11.74	< .001
Excluded Variables								
	Shared Features					-.04	-.58	0.57
	Proximity X Shared Features					-.10	-.31	0.76

Discussion

Like ELM (Arguin et al., 1996), normal observers did not show an effect of shared features in a perceptually demanding task. Neither participant accuracy nor response time varied significantly between the two object set conditions, suggesting that, all else being constant, parallel object relationships do not show an effect in this task (although see Arguin & Saumier, 2000 for a different account). Results from the regression analysis support this finding, showing that dimensionality has no significant predictive capacity for participant error in a task designed to assess perception. It may be that shared features have a greater (detectable) impact in tasks that place more strain on memory. To test this assumption the next two experiments (1b and 1c) were conducted.

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uncorrelated (Field, 2009). See Durbin and Watson's original paper (DURBIN & WATSON, 1951) for a more in depth explanation.

Lack of an effect of shared features in a perceptually demanding task. That normal observers showed no effect of shared features in a perceptually demanding task is somewhat puzzling. Although these findings are congruent with findings from work with CSVA patient ELM (Arguin et al., 1996; Dixon et al., 1997), they appear to be inconsistent with other studies that do in fact find behavioral differences in tasks of feature integration during perception (Arguin et al., 1996; Blais et al., 2009). A regression analysis of the data from Experiment 1a reveals that shared features did not significantly predict participant errors. However, if integration of structural features was necessary to perform the task, shared features should drive participant errors, but only if the task exceeded participants ability to perform optimally (i.e. participants were not at ceiling). Moreover, the results of the regression analysis suggest that proximity was the only significant predictor of participant error in a perceptually demanding task, and considering proximity between the square and object sets is equated, a non-significant difference in performance between the two object sets should be expected. But this does not address the question of how structural features must be integrated during perception.

Participants in Experiment 1a did not show a significant number of integration errors (as evidenced by the lack of difference between accuracy scores for the two experimental conditions). Further, the results of the regression analysis suggest that any errors participants did make were not the result of a failure to integrate features, but due to proximity. That participants were given an unlimited amount of time to respond in Experiment 1a could explain the lack of integration errors. Perhaps, the task did not put enough pressure on the integration system to elicit integration errors. Our task tested for an effect of integration by looking for failures of integration. It could be that assessing response times – which shows the temporal cost of integration – may be a better way to test the presence of integration during perception.

Arguin and Saumier (2000) show a response time difference between a Conjunction task and a No-Conjunction task (Figure 4) in a visual search paradigm, with the Conjunction sets requiring more time to disambiguate (see above). Arguin and Saumier reason that because the Conjunction set requires integration of feature information and the No-Conjunction set does not, the extra time necessary in the Conjunction task reflects this additional step. These results suggest that response time may be able to more sensitively assess the role of integration during perception, however a number of differences exist between their experiment and ours. First, Arguin and Saumier had participants norm their stimuli so that they were *perceived* as equidistant in an adjustment task. Thus, even if these psychological distances do reflect equal physical object distances, their stimuli are assumed to be more distal along diagnostic dimensions than are ours. This conjecture is supported by the fact that Arguin and Saumier assessed reaction time (as accuracy was presumably near ceiling for both conditions). That is, participants' high accuracy in their study was likely due to large object dissimilarities resulting from greater inter-object distances than were utilized in our design (which purposefully crowded objects to elicit participant error). As such, it is possible that the relative crowding of stimuli in our object set put such a high demand on resolution of distance that any effect of shared features was masked.

Increasing inter-object proximity, such that resolving competition due to crowding becomes increasingly difficult, could mask the effect of shared features. For instance, if the majority of errors made in Experiment 1a were a result of the crowded nature of our stimulus, the remaining effect of shared features may have been too small to detect with our relatively small sample size. Rather than adding more participant data to Experiment 1a in the hopes of resolving this hypothesized conflict, a new study was devised that more sensitively assessed the effect of integration during perception. Specifically, the goal of Experiment 1a was to assess whether integration in a perceptually demanding task influences object similarity. Finding no difference in similarity between a diamond and square object set, we resolved to assess whether integration does in fact occur during perception (see Experiment 2).

Experiment 1b

This paradigm is quite similar to the location memory task utilized with ELM (Arguin et al., 1996). Thus, it is hypothesized that, like ELM, normal observers will show a marked deficit in recalling objects with a large number of shared features. However, unlike ELM's task, our paradigm controls for inter-object proximity in physical space. It is assumed that the square object set (which contains a greater number of parallel object relationships) will show poorer recall accuracy than the diamond object set. Further, by conducting a linear regression analysis on participant errors we expect to find that while proximity is still a strong predictor of participant error, the effect of shared features will be significant. Lastly, if a significant difference in accuracy is found between the diamond and square object set, a series of chi-squared analyses will be conducted to determine whether parallel errors are proportionally more prevalent than diagonal errors. This would support our assumption that shared features increase inter-object similarity above and beyond what can be accounted for by physical proximity alone.

Method

Participants. 49 volunteers from the University of Richmond participated in Experiment 1b. Participants ranged in age from 18 to 22 and possessed either normal or corrected vision. Recruited participants were compensated either with course credit (2 credits/hour) or with cash ($10/hour) for their participation. Other participants completed the experiment as an in-class activity for a Cognitive Neuroscience course. These participants had the option of whether or not to submit their data for review. This method of participation was approved by the University of Richmond's IRB prior to testing. All participants were treated in accordance with the ethical standards of the APA.

Materials. The objects used in this experiment are the same that were used in Experiment 1a.

Design and Procedure. Unlike Experiment 1a, Experiment 1b required participants to hold all eight objects in an object set and their locations online in working memory. Participants were randomly assigned to either the diamond or square object set to prevent generalization of learning, as both sets require attention to the same two dimensions. Participants were first shown all 8 objects within an assigned object set. The eight objects within the object set corresponded to the 8 outer blocks of a 3x3 grid. The locations were numbered in a fashion that corresponded to a keyboard number pad, omitting the number 5. There were two possible random assignments of objects to locations, which was counterbalanced across participants and object sets. The location assignments were consistent for a participant across blocks. Each block consisted of a study phase, in which all 8 objects appeared together on the screen for one minute, followed by 16 test trials. During test trials participants were presented with a single object from the studied group in the center of the screen and asked to respond by pressing the number key corresponding to the objects location in the study set. Participants were given an unlimited amount of time to respond. Between test trial a 100 millisecond mask was presented to clear the image on the retina. Each participant completed 8 blocks of 16 trials with the to-be-studied object set appearing at the beginning of each block. The experiment was run on a Macintosh computer using Superlab 4 software.

Results

Accuracy. An independent samples *t*-test was conducted to evaluate the effect of shared features on normal object recall of an object as measured by response accuracy. The *t*-test was significant, $t(47) = 2.04$, $p < 0.05$, indicating that the mean accuracy of 0.44 (SD = 0.21) for the square object set is significantly less than the mean accuracy of 0.54 (SD = 0.15) for the diamond object set.

Regression. A multiple regression analysis was conducted to see if inter-object proximity in physical space, shared features, and/or the interaction of the two variables could significantly predict the number of participant errors in each of the two object set conditions. As this regression is primarily exploratory in its objectives and the importance of each predictor is unknown, a forward, step-wise regression method is utilized. The results of this analysis are presented in Table 2. The Durbin-Watson statistic for the model is equal to 1.67, suggesting an acceptable amount of correlation amongst residuals. Both proximity and shared features are found to be significant predictors of the number of participant errors, with a model including both (model 2) accounting for the largest amount of variance (56%).

Table 2. Summary of the forward, step-wise regression analysis in which the pairwise confusion data of Experiment 1b was regressed onto proximity, shared features (coded as 1 = a shared feature and 2 = no shared features) and their interaction.

		Model statistics				Standardized Coefficient Statistics		
		F	*p*	R^2	Durbin-Watson	*β*	*t*	*p*
Model 1		127.56	< .001	0.53	1.68			
	Proximity					-.73	-11.29	< .001
Model 2		70.40	< .001	0.56	1.68			
	Proximity					-.70	-10.75	< .001
	Shared Features					-.17	-2.58	< .05
Excluded Variables								
	Proximity X Shared Features					-.10	-.31	0.76

Chi-Square. Two one-sample, chi-square analyses were conducted to assess whether the number of observed pair-wise error types (parallel-tapering, parallel-pinching or diagonal) were distributed differently than would be expected by chance, given the number of parallel relationships that exist in each set. Separate chi-square analyses were conducted for the two object sets. The results of the analysis for the square object set are significant, $\chi^2(2, N = 1716) = 71.65$, $p < 0.001$. The number of parallel-pinching (509) and parallel-tapering errors (683) were significantly higher than expected (429), while the number of diagonal errors (524) was significantly less than expected (858). The results of the analysis for the diamond object set are also significant, $\chi^2(2, N = 1451) = 40.22$, $p < 0.001$. The number of parallel-tapering errors (217) was significantly higher than expected (155.5), while the number of parallel-pinching (106) and diagonal errors (1128) were significantly less than expected (155.5 and 1140.1, respectively).

Discussion

The results of Experiment 1b indicate that the recall accuracy for the square object set is significantly worse than that of the diamond object set. As the objects sets only differ by total number of shared features, this experiment provides strong support for the role of shared features in a task that puts a high-strain on working memory (i.e., participants had to hold the locations of 8 objects online across 16 probe trials). To further assess the contribution of inter-object distances within object sets, a regression analysis was run to assess the unique contributions of inter-object proximity and shared features as well as any possible interaction between the two. The regression equation predicted a strong effect of proximity on number of errors, with decreasing inter-object distance predicting more recall errors. Importantly, in addition to proximity, shared features were found to be a significant predictor of participant error as well, with more shared features predicting more recall errors. These results support our assumption that shared features increase inter-object similarity above and beyond what can be accounted for by physical proximity alone. Thus, in this task, shared features do indeed serve a significant role in the correct recall of an object (albeit subordinate to the effect of proximity in physical space).

Further evidence that participant errors are modulated by shared features is provided by the two chi-squared analyses run on the data from the diamond and square object sets. Thus, although overall performance on the task is superior for the diamond object set, both object sets display a marked deficit of recall for objects with a parallel relationship relative to diagonal ones[5]. The disproportional difficulty of parallel objects

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[5] While both the parallel/pinching and parallel/tapering errors are disproportionately large for the square object set, only the number of parallel/tapering errors were inflated in the

suggests that some confusions were caused by a failure to integrate one of the diagnostic features.

Experiment 1c: Long-term recall

Experiment 1b demonstrates that shared features effect object similarity at recall such that an object set with a larger number of shared dimensions (square object set) showed more object confusions than a set with fewer shared features. Whether shared features would have the same effect when objects are committed to long-term storage is a question left unanswered. Thus, a task that requires long-term storage of the object dimensions was devised.

Given that ELM showed difficulty with objects that shared structural features in a long-term recall task, we predict that normal observers will show difficulty with objects possessing shared features in a similar task of recall. Therefore, as in Experiment 1c, we hypothesize that confusions due to parallel relationships will be observed in a long-term recall task as well. We utilize a procedure similar to that of Bukach et al. (2004) in which a surprise recall task is used that requires participants to bind the object attribute of color to each of the objects in a set. Not unlike the feature of location information learned in Experiment 1b, the feature of color is used to allow assessment of recall for an object set following an incidental learning paradigm. As before, recall for the square configuration set (more parallel relationships) should be poorer than for the diamond configuration set. Further, results of a regression analysis on participant errors is expected to show an effect of shared features over and above the effect of proximity. Lastly, a series of chi-squared

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diamond set. See the General Discussion section of this paper for a dialogue on this finding.

analyses will be conducted to determine whether parallel errors are proportionally more prevalent than diagonal errors. This would support our assumption that shared features increase inter-object similarity above and beyond what can be accounted for by physical proximity alone.

Method

Participants. 35 volunteers from the University of Richmond participated in Experiment 1c. Participants ranged in age from 18 to 25 and possessed either normal or corrected vision. 25 of the 35 participants were recruited from the Psych 100 pool and were compensated with course credit (2 credits/hour). The remaining 10 participants were recruited from the general student population and were compensated ten dollars (equivalent to the rate of $10/hour) for their participation. Two participants were excluded when it was later discovered that they had had previous exposure to the stimuli leaving 33 participants.

Materials. Stimuli were the same as in Experiments 1a and 1b, with the exception that each object in the square and diamond object set was rendered in eight colors using Photoshop. The eight colors (blue, brown, green, pink, purple, red, teal and yellow) were assigned to different objects. Further, eight different object sets were created using the diamond and square object sets such that each object was rendered in every color. Participants were randomly assigned to one of these 16 object sets.

Design and Procedure. Experiment 3 utilizes a verification task, which required participants to recall arbitrary perceptual information (i.e., color) previously paired with an object. Participants were randomly assigned to either the diamond or square object set to prevent generalization of learning, as both sets require attention to the same two dimensions. Before participants began the training phase of the experiment, a brief color-naming task was presented to ensure that participants could correctly label the eight colors used in the experiment. Participants had to reach a criterion of 100% accuracy on the color-naming task before proceeding to the training task.

The training task asked participants to study two colored stimuli for 1500 milliseconds. Next one of the previously presented objects was shown in gray-scale along with a color label (e.g., blue), and the participant was asked to judge whether or not that color was attributed to the gray-scale object in the previous presentation. This screen was displayed until the participant responded using the “n” (non-match) or “m” (match) keys on a standard Macintosh keyboard. The participant had 5000 milliseconds to respond. A 1000 millisecond inter-trial interval was presented after each response. Object pairs were randomized with constraints such that every object in the set appeared with every other object in the set an equal number of times. The side of the screen on which the target object was presented and whether the trial was a match or non-match situation was also randomized. Unbeknownst to the participants, each object was always presented in the same, unique color. Participants completed at least 7 blocks of 32 trials before moving on to the test phase of the experiment. However, at the seventh block (as well as all subsequent blocks), participants were required to reach a criterion of 85% accuracy before moving on to the test phase of the experiment.

Following successful completion of the training phase, participants were presented with a surprise color verification task that required access to long-term memory. Thus, object competition came from all objects in the set, rather than just a single object (as in the training phase). In this way, shared features should affect performance during the test phase of the experiment but not the training phase. Participants were again shown each gray-scale stimuli one at a time and had to recall the color of each object as it was previously depicted during training. However, without the color prompting available to participants in the training phase, participants had to access long-term memory to correctly recall the objects color. As in the training phase, participants were shown the previously presented objects in gray-scale along with a color label, and asked to judge whether or not that color was attributed to the gray-scale object in previous trials (again using the "m" and "n" keys). Participants had 5000 milliseconds to respond. The test phase consisted of 14 blocks of 16 trials, in which correct response (match or non-match) and target object were randomized. The experiment was run on a standard Macintosh computer using Superlab 4.

Results

Sensitivity. An independent samples *t*-test was conducted to evaluate the effect of shared features on normal long-term recall of an object set as measured by the sensitivity statistic[6]. Averages of sensitivity (*d'*) were calculated for the diamond object set and the square object set groups, and used as input data for the *t*-test. The *t*-test was significant, $t(31) = -2.26$, $p < 0.05$, indicating poorer performance with the square condition (mean *d'* = 1.38, $SD = 0.66$) relative to the diamond object set (mean *d'* = 1.87, $SD = 0.58$).

Regression. A multiple regression analysis was conducted to see if proximity, shared features, and/or the interaction of the two variables could significantly predict the number of confusions for each possible object pair. Again, a forward, step-wise

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[6] Sensitivity (*d'*) is a more precise measure of accuracy, independent of bias, which is based upon signal detection theory. Sensitivity accounts for bias by accounting for false alarms.

regression method is utilized. The results of this analysis are presented in Table 3. The Durbin-Watson statistic for the model is equal to 1.55, suggesting an acceptable amount of correlation amongst residuals. Both proximity and shared features are found to be significant predictors of the number of participant errors, with a model including both (model 2) accounting for the largest amount of variance (49%).

Table 3. Summary of the forward, step-wise regression analysis in which the pairwise confusion data of Experiment 1c was regressed onto proximity, shared features (coded as 1 = a shared feature and 2 = no shared features) and their interaction.

		Model statistics				Standardized Coefficient Statistics		
		F	*p*	R^2	Durbin-Watson	*β*	*t*	*p*
Model 1		83.04	< .001	0.43	1.60			
	Proximity					-.66	-9.11	< .001
Model 2		53.88	< .001	0.49	1.60			
	Proximity					-.59	-8.46	< .001
	Shared Features					-.27	-3.81	< .001
Excluded Variables								
	Proximity X Shared Features					-.36	-3.03	< .01

Chi-Square. Two one-sample, chi-square analyses were conducted to assess whether the number of observed error types (parallel-tapering, parallel-pinching or diagonal) were proportionally equal to the number of parallel-tapering, parallel-pinching and diagonal relationships in each object set. Separate chi-square analyses were conducted for the two object sets. The results of the analysis for the square object set are significant, $\chi^2(2, N = 657) = 87.82$, $p < 0.001$. The numbers of parallel-pinching (168) and parallel-tapering errors (261) are significantly higher than expected (164.2), while the number of diagonal errors (228) is significantly less than expected (328.5). The results of the analysis for the diamond object set are also significant, $\chi^2(2, N = 393) = 21.45$, $p < 0.001$. The number of parallel-tapering errors (66) is significantly higher than expected (42.1), while the numbers of parallel-pinching (24) and diagonal errors (303) are significantly less than expected (42.1 and 308.8, respectively).

Discussion

As in Experiment 1b, the results of Experiment 1c indicate that the accuracy of recall for the square object set was significantly worse than that of the diamond object set. To assess the contribution of inter-object distances within object sets, a regression analysis was run to assess the unique contributions of physical proximity and dimensionality as well as any possible interaction between the two. As in Experiment 1b, the regression for Experiment 1c predicts a strong effect of proximity on number of errors, with decreasing inter-object distance predicting more recall errors. Further, shared features are a significant predictor of participant error as well, with more shared features predicting more recall errors. Thus, like ELM, participants showed difficulty with those objects that shared features in our long-term recall task. Therefore, shared features must again serve a significant role in the correct recall of an object (still subordinate to the effect of proximity in physical space).

Further consistencies between the results of Experiment 1b and 1c are provided by chi-squared analyses, which provide evidence that participant errors were disproportionately made on trials that involved parallel relationships. Although overall performance on the task was superior for the diamond object set, both object sets displayed a marked deficit of recall for objects with a parallel relationship relative to diagonal ones. The disproportional difficulty for objects with parallel relationships suggests as the number of shared features increases recall performance decreases. However, as in experiment 1b, both the parallel-pinching and parallel-tapering errors are disproportionately large for the square object set, but only the number parallel-tapering errors were inflated in the diamond set. See the General Discussion section of this paper for a dialogue on this finding.

Having completed our three intended studies, we find that shared features do in fact alter interpretations of similarity, and to a varying degree depending on task demands. However, across Experiments 1b and 1c there were more errors for tapering than pinching (cf. chi-squared analyses for Experiments 1b and 1c). This suggests one of two possibilities: 1.) tapering is more difficult than pinching; or 2.) tapering is less salient than pinching. To address this ambiguity a stimulus manipulation check was designed to test the relative difficulty of the two dimensional manipulations independently, in an attempt to rule out the difficulty explanation.

Stimulus Manipulation Check

To assess whether the increments of change along the tapering and pinching dimensions are not just physically equivalent but perceptually equivalent as well, a task was designed to test our structural dimensions separately. Assuming that the units of change for both the tapering and pinching dimensions are perceptually equivalent, performance on a tapering task and a pinching task should be equivalent as measured by participant accuracy. Therefore, based upon our assumption of equal dimensional salience, there should be no significant difference between accuracy for the two dimensions. However, some findings from our study suggest that the two diagnostic structural dimensions were not treated equally by participants. In our chi-squared analyses from the memory tasks (Experiments 1b and 1c), only parallel-tapering errors were inflated (greater than could be expected by chance) for the diamond object set (for the square object set both parallel-pinching and parallel-tapering errors were inflated). This suggests that the tapering dimension caused slightly more problems for participants.

The simplest explanation of these results (and therefore the one preferred by the authors) is that the tapering dimension, which appears at the top of the object (see Figure 5) is further from the fixation point than the pinching dimension (which is located in the center of the object). As a result, participants may have preferentially attended to the pinching dimension, as it is more central in the figure and closer to fixation. Thus, parallel-tapering errors alone may have driven confusions with the diamond object set in the memory tasks, because the tapering dimension was not as salient or not as well attended to. As such, we predict that tested singly, the pinching dimension may be treated preferentially by participants. Implications for our findings will be addressed in the discussion section.

Method

Participants. 16 volunteers from the University of Richmond participated in the stimulus check. The participants ranged in age from 19 to 24 and possessed either normal or corrected vision. Participants were compensated with either course credit (2 credits/hour) or with cash ($10/hour).

Materials. Two sets of five gray-scale, 3D objects rendered in two textures using Carrara 5 pro (Figure 7), were used in the stimulus check. The objects within each set varied along a single structural dimension, all other structural properties were held constant. Also, all five objects were rendered in one of two textures (crater and gravel); however, as before data were collapsed across texture and will not be discussed. The two structural dimensions manipulated in the stimulus check were pinching and tapering. The physical distance between any two objects in a set was equal for both the pinching and tapering object set. As the stimuli varied on only a single dimension, this inter-object proximity was equal to a single unit of change along the diagnostic dimension. Furthermore, to ensure that the inter-object distance between stimuli in this experiment were equal to the smallest possible increment of change along a single structural dimension, increments were equal to the smallest inter-object distance along a single dimension in the diamond object set (i.e., the length of a single leg of a superimposed right triangle – not the hypotenuse; see discussion of a city-block metric above). As such, inter-object distance in the stimulus manipulation check was smaller than inter-object distance in Experiments 1a, 1b, and 1c, as assessed by Euclidean distance. While this increased crowding of stimuli in the stimulus check relative to the above three experiments may have increased participant errors, it should not have effected the relative saliency of our two structural dimensions.

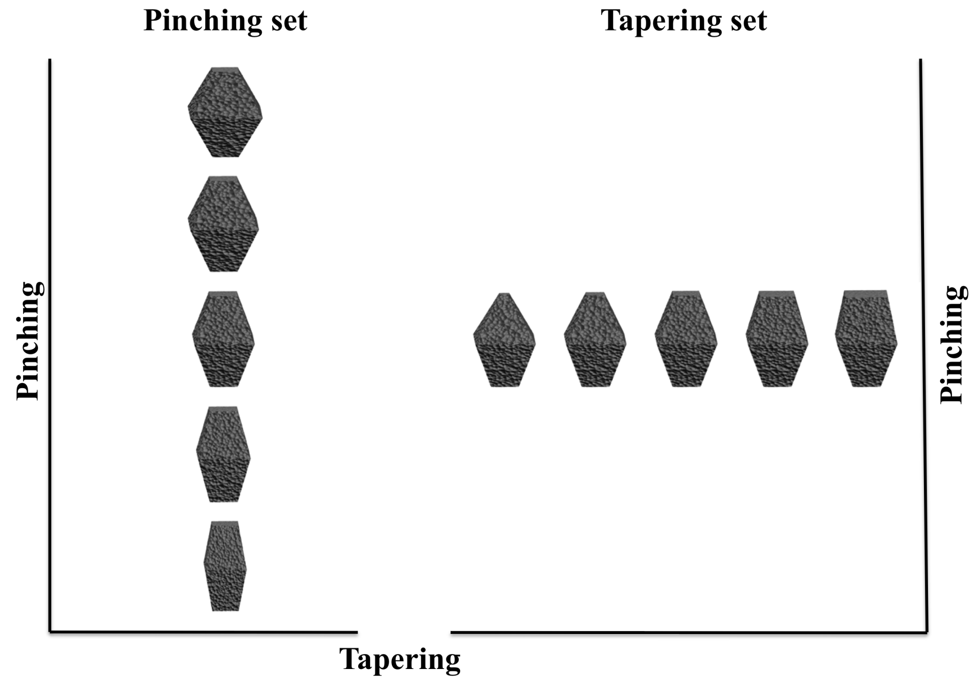

Figure 7. Stimuli from the pinching and tapering object sets graphed according to values of tapering and pinching. Proximity is controlled for between the two object sets, such that any two objects in both the pinching and tapering set are equidistant.

Design and Procedure. A match to sample design was utilized such that participants had to match a single object to a set of five. Participants were first presented with a fixation cross for 500 milliseconds followed by the target stimulus. The target stimulus was viewable for 2000 milliseconds, after which a mask was shown for 500 milliseconds to clear the image on the retina. Following the presentation of the mask, the entire subset of five objects, numbered 1-5, appeared on the screen. The objects were randomly assigned to one of five positions in a trapezoidal configuration (i.e, a row of two objects above a row of three objects) on each trial. The participant was given an unlimited amount of time to identify the target stimulus using the number pad on a standard Macintosh keyboard. The experiment was blocked by object subset (e.g., pinching/gravel). There were 8 experimental blocks of 25 trials each. Texture alternated every block, while diagnostic dimension alternated every two blocks in an ABBA design.

Order of blocks was counterbalanced between subjects. The experiment was run on a Macintosh computer using Superlab 4 software. Accuracy was used as the dependent measure of interest.

Results

Accuracy. A paired-samples *t*-test was conducted to evaluate the effect of diagnostic dimension (pinching or tapering) on accuracy. The *t*-test was significant, $t(31) = -2.38$, $p < 0.05$, indicating that the mean accuracy of 0.63 (SD = 0.15) for the pinching object set is significantly less than the mean accuracy of 0.68 (SD = 0.11) for the tapering object set.

Discussion

The results of the stimulus check are contrary to our original hypothesis. Participants exhibited fewer errors for the tapering set than for the pinching set. This is opposite of the findings discussed from the chi-squared analyses performed on the data from Experiments 1b and 1c (see above). Interestingly, when tested singly during a perceptually demanding task, participants were more accurate with the tapering (above fixation) dimension. When tested with the same dimensions simultaneously in two tasks that place the demand on memory (Experiments 1b and 1c) the opposite effect is found: Participants were more accurate with the pinching (at fixation) dimension.

These somewhat surprising findings find support from the just noticeable difference literature. That is, the saliency of a single unit of change is proportional to the ratio of unit change to total magnitude (Palmer, 1999). Thus, a single unit of change along the tapering dimension should be more salient than the same unit of change along the tapering dimension, because the ratio of unit change to total magnitude is greater for the tapering dimension. This explains the results from our stimulus manipulation check, but the opposite results were found in our memory tasks (Experiments 1b and 1c). Thus, it seems that the saliency of the structural dimensions (or perhaps how they are attended) is task-dependent. The difference in confusability between 1D and 2D sets provides further evidence that similarity cannot be accounted for by simple proximity measures in physical space, and that object categories that vary on multiple diagnostic features are better modeled by distributed representations in which attention and integration of features are dynamically determined by a variety of factors. Thus, that perceived inter-object distance (in psychological space) appears to be task dependent actually provides support for our theory that physical proximity alone is not sufficient to predict similarity judgments.

EXPERIMENT II

While the integration of visual features from multiple visual domains (e.g., color, orientation) has been well studied (Cortese, Bernstein, & Alain, 1999; Paz-Caballero & García-Austt, 1992; Treisman & Gelade, 1980 to name a few), the role of structural feature integration has received relatively little attention. The three experiments recounted above highlight an effort to address the integration of structural features and the role of shared structural features during perception and at recall. We have demonstrated that in tasks involving recall (Experiments 1b and 1c) structural features need to be integrated, as evidenced by participants' difficulty distinguishing objects with shared diagnostic features. Shared object features should only cause participant errors if object features are stored separately and need to be integrated at recall. However, no effect of shared features was detectable in our perceptually demanding task (Experiment 1a). While these results could be interpreted as drawing support for an account of object recognition that does not require integration during perception, such an interpretation bears little support from the extant literature (see above) and we believe our inability to find an effect of shared features in this task is a result of the insensitivity of our paradigm. One way of achieving a more sensitive measure of the time course of integration during perception is to utilize electrophysiology. Before discussing some relevant literature, a brief overview of electrophysiology (insofar as it pertains to our study) will be presented.

Electrophysiology

Electrophysiology is a method by which the electrical signals from cells are recorded. Of particular interest to our lab are readings from neurons near the scalp using an electroencephalogram (EEG). As brain neurons near the scalp respond to events and task demands, the electrical signals produced by the neurons can be measured by sensors placed on the scalp, resulting in a wave that fluctuates over time between negative and positive polarity at each sensor. The particular type of electrophysiology that is utilized in the following study is generally referred to as an Event-Related Potential (ERP). This methodology measures the waveforms produced by each electrode placed on the scalp from the time of an event (e.g., presentation of a stimulus) for about 800 to 1000 ms after the event is presented. Because the changes in waveforms between conditions can be very small, many trials from each condition are averaged before comparing differences between conditions. Because ERPs measure summed activity from all neurons, it is very difficult to localize where the change in signal originates. However, the temporal resolution available through ERP measurements is in the order of milliseconds. As such, this technique will tell us about the specific timing of the featural integration processes, and through comparisons of different conditions, can tell us about how differences in task demands or stimulus properties affect the process. Specifically, an average waveform of electrical activity can be achieved across participants for each condition. These averages can be subtracted from one another to create a difference wave. Assuming all possible confounding variables are controlled for, a difference wave will show only those portions of the waveform that differ between conditions. This difference wave will reflect any differences in processes between conditions.

The following study (similar to those presented below) will rely heavily on the presence of a commonly observed component of the ERP waveform known as the P3.

The P3 component (or more specifically the P3b component) is task-dependent in that it will appear in response to any designated target object. For instance, if a task requires participants to respond to Xs when presented serially amongst Ys and Zs, a P3 component will be observed in the data from trials that contain Xs. Further, the magnitude of the P3 increases relative to the frequency of a target being presented, such that as the likelihood of a target decreases the P3 amplitude increases (Johnson, 1986; Luck, 2005). Thus, using the previous example, if 10% of trials contain an X, the resultant P3 component will be larger than if 50% of trials contain an X. The P3 component is of interest to us because it represents a predictable difference between average waveforms of targets and distracters. For instance, assuming all else is constant in a serially presented stream of stimuli, the only difference between an average waveform for target trials and distracter trials will be the P3. Therefore, a difference wave (subtracting the distracter trial waveform from the target trial waveform) will isolate the P3. At this point the data is of particular interest for assessing the time course of an integration process. That is, if the P3 for conjunction trials and single feature trials can be isolated, they can be compared. Visually this is accomplished by creating another difference wave. The difference wave of the two isolated P3 component waves will reveal the time course of integration insofar as it affects the latency of the P3 because the P3 is not elicited until the stimulus is identified and categorized as a target. Computationally, the mean peak latencies of the P3 (defined as the peak latency within a time window) for each of the conditions can be directly compared using statistical methods. For conjunction trials, this would be contingent upon the integration process preceding the process reflected in the P3 component. But, the P3 component is task dependent, which means a stimulus must be categorized as a target in order to elicit a P3 (Kutas, McCarthy, & Donchin, 1977; Magliero, Bashore, Coles, & Donchin, 1984), and therefore any integration process would have to precede this categorization of an object as a target. If integration of features is necessary to distinguish a target from a possible distracter, this integration process will necessarily precede the process associated with the P3, and therefore delay the latency of this readily identifiable component only in the conjunction condition.

Also of interest in our study is the lateral occipital subcomponent of the N1 wave, which typically peaks between 150-200 ms post stimulus (Luck, 2005). Evidence suggests that spatial attention influences the N1 subcomponent in general (Luck, 2005). In addition, the lateral occipital subcomponent of the N1 responds more strongly in discrimination tasks than in detection tasks (Vogel & Luck, 2000). Because of it's early placement in the ERP waveform and its involvement in early perceptual processes we will analyze the N1 component to determine if there are any early perceptual differences among waveforms that may implicate an integration process. That is, by analyzing the mean amplitude and peak latency (see above) of the N1 component by condition we will be able to detect any early wave differences between conditions. If there is a significant difference in (either latency or amplitude of) the N1 between conjunction trials and single feature trials this might suggest that an integration process occurs as early as the appearance of the N1wave.

Background

In a study utilizing behavioral and electrophysiological data, Cortese, Bernstein and Alain (1999) were able to show the need for integration in a perceptual task when targets had to be indentified on the basis of multiple diagnostic features. Cortese et al. had participants search for targets among serially presented bars that varied by color (blue and purple) and orientation (vertical and horizontal). In a single feature condition participants were asked to respond to a single feature and ignore the irrelevant dimension (e.g., respond to all blue bars, whether horizontal or vertical). In a conjunction condition, participants were tasked with identifying only objects with a specified value for each diagnostic dimension (e.g., respond to all vertical blue bars and nothing else). Thus, in the single feature conditions attention to a single dimension was sufficient to perform the task and, as a result, integration of the two diagnostic structural features was unnecessary. In contrast, the only way to successfully complete the conjunction condition was to integrate the two diagnostic structural dimensions (i.e., know that a target was defined as being blue and being vertical). The authors found that not only did participants take significantly longer to respond to stimuli in a conjunction condition, accuracy was poorer for the conjunction set (relative to the two single feature conditions). Furthermore, compared with the ERP waves from target trials in the single feature condition, ERP waves from target trials in the conjunction condition showed an increased (negative) magnitude between 230 and 270 ms post-stimulus at midline frontal, central and parietal sites. The P3 latency was also delayed in the conjunction condition relative to the color condition. Importantly though, when comparing target and distracter trials for the conjunction condition, Cortese et al. found an increased (positive) magnitude at frontal and central sites at about 180 ms (preceding the P3 component). This difference represented the earliest point at which the conjunction and single feature conditions differed and therefore may indicate the point at which an integration process takes place.

Cortese et al. interpret these results as evidence for two processing stages involved in perception: one specific to individual features and one specific to the conjoining (or integrating) of features. Thus, behavioral data suggests that when an extra process (integration) is necessary for a task, responses will be slower. These findings corroborate with those of Arguin and Saumier (2000) who found a similar effect of featural integration during recall on response time. Further, when multiple dimensions are diagnostic in resolving conflict between objects, accuracy will suffer (relative to a task that does not require featural integration). Although not specifically mentioned by Cortese et al., the sharing of diagnostic features between distracters and targets may have driven this poorer accuracy for the conjunction condition. Lastly, electrophysiological data show that a difference in neuronal firing patterns is observed between the single feature and conjunction conditions at around 180 ms post stimulus presentation. This event is interpreted as representing an integration process. Similar results have also been shown by Paz-Caballero and Garcia-Austt with shape and location dimensions (Paz-Caballero & García-Austt, 1992). However, no study has assessed the integration of two structural features using electrophysiology.

To better understand how structural features are integrated at recall, an electrophysiological test of perceptual integration was developed using a method similar to that employed by Cortese et al. (1999) and Paz-Caballero and Garcia-Austt (1992). However, rather than explicitly instructing participants about the features to be identified, participants implicitly determined the most successful criteria for distinguishing targets and distracters (see below). Another improvement over the previous work is that we have controlled for number of targets (all conditions have 2 targets). Cortese, et al. confounded number of targets with conditions such that there were essentially two targets in each of the single feature conditions (e.g., blue vertical AND blue horizontal) but only one in the conjunction condition (e.g., blue vertical). Having a varying number of targets relative to distracters impacts the magnitude of an elicited P3 for target trials (Luck, 2005), introducing uncontrolled variance between conditions. While Cotese, et al. control for the total number of target trials in each condition, their actual number of targets varied by condition which may have accounted for their results. The current study controls for this possibility.

For Experiment 2 we utilized four objects from our existing stimulus sets, which form a square when plotted in physical space (see Figure 8). By utilizing four such objects and simply manipulating which stimuli were labeled as targets and which were labeled as distracters in a serially presented match/non-match task we were able to ensure that integration was necessary in a conjunction condition (i.e., participants could not successfully complete conjunction trials by attending to one feature at a time), but not in a single feature condition. For instance, if two objects from the set of four that share a feature for pinching are labeled as targets (see Figure 8A) and the other two objects (which share a different feature for pinching) are labeled as distracters, only pinching need be attended to when identifying the stimuli later on (a single feature condition). However, if two objects from the set of four that do not share a feature for either tapering or pinching are labeled as the targets (and the remaining two objects which also do not share a feature for tapering or pinching are labeled as distracters; see Figure 8B) than the only way to determine whether any given object from the set of four is a target or a distracter is to integrate the features of the object at perception. Specifically, a single feature is not sufficient to identify either of the targets, because every single target feature is shared with one of the distracters. Thus, in this conjunction condition, a target is defined as a specific pair of features, rather than the presence of a single diagnostic target feature (see Figure 8).

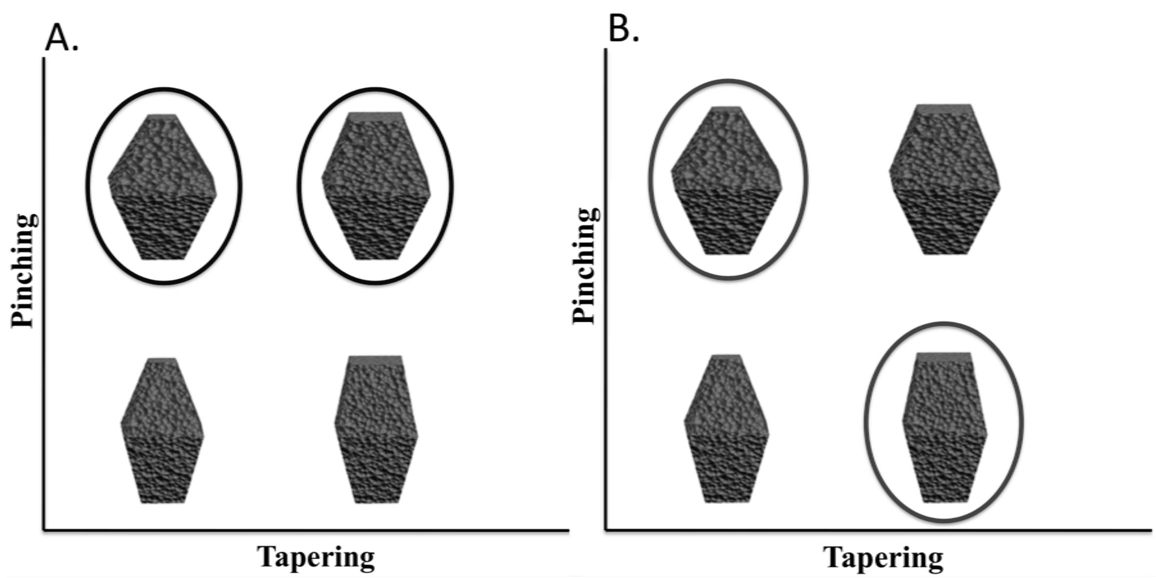

Figure 8. Model of stimuli design for Experiment 2. In A.) the two designated targets (incircled) share a feature along the pinching dimension and can thus be distinguished from the other two objects in the set of 4 (distracters) on the basis of a single dimension – the diagnostic (target) feature for pinching. Contrastingly, in B.) the two designated targets (incircled) do not share features on either of the two structural dimensions. Therefore, in order to distinguish the targets from the distracters in this set a participant must integrate featural information from the two structural dimensions before identifying any of the stimuli as a target or distracter.

Importantly, regardless of the condition (conjunction or single feature) there are always two targets and two distracters. By ensuring that there were two targets in every trial we not only controlled the number of target stimuli from trial to trial but also ensured that feature integration was necessary in the conjunction condition but not in the single feature conditions. Further, similar to the previous studies, the task context was a set of 4 objects, thereby avoiding simple pairwise effects of similarity that would drive similarity in a pairwise sequential matching task.

Pilot Study

Before running the full version of Experiment 2 (with electrophysiology) we conducted a pilot study using the behavioral paradigm used in Experiment 2 to determine an optimal set of stimuli for the experiment. That is, we had the option of using the four stimuli that form the "corners" in the square object set (objects a, c, g and e from the square object set; see Figure 6) or the four inner stimuli from the diamond object set (objects b, d, f and h from the diamond object set; see Figure 6). As we wished to utilize a stimuli set that was neither too difficult (i.e., at chance) nor too easy (i.e., at ceiling) we set an a priori criterion of 70 – 85% accuracy for whichever stimulus set we intended to use. Thus, because we were not only interested in the electrophysiological data that could be attained in Experiment 2, but also behavioral data (e.g., accuracy and response time) we wanted to ensure that our stimuli set would challenge participants' abilities enough to elicit some behavioral error, while also ensuring that enough correct trials could be attained to be used in electrophysiological analyses. As such, we decided to use whichever stimuli set yielded a participant accuracy in the range of 70 – 85%.

Method

Participants. 16 individuals from the University of Richmond between the ages of 18 and 22 participated in the pilot of Experiment 2. Participants were compensated with either two PSYCH 100 credits or $10 (at a rate of $10/hr).

Materials. The four inner stimuli from the diamond object set (objects b, d, f and h from the diamond object set; see Figure 6) made up the stimuli in the "proximal" condition. The four "corner stimuli" from the square object set (objects a, c, g and e from the square object set; see Figure 6) made up the stimuli in the "distal" condition.

Design & Procedure. For the pilot study we used a procedure identical to the one to be used in the full version of Experiment 2. For this reason, much of the procedure was designed to optimize ERP recordings and may seem extraneous for a behavioral paradigm. Those aspects of the procedure that are intended to maximize the success of an ERP experiment will be discussed in more detail in the Main Study section below.

Participants were randomly assigned to either the proximal or the distal object set and to one of two counterbalanced conditions that control for assignment of stimuli to target and distracter conditions [7]. For Group A the targets in the single dimension (tapering) condition were h and f (Diamond, Figure 6) for the proximal condition and a and g (Square, Figure 6) for the distal condition. The targets in the single dimension (pinching) condition were h and b (Diamond, Figure 6) for the proximal condition and c and e (Square, Figure 6) for the distal condition. Lastly, the targets in the conjunction condition were f and b (Diamond, Figure 6) for the proximal condition and g and c (Square, Figure 6) for the distal condition. For Group B the targets in the single dimension (tapering) condition were b and d or c and e (Diamond and Square, respectively), the targets in the single dimension (pinching) condition were f and d or a and g, and the targets in the conjunction condition were h and d or a and e.

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[7] The two experimental groups are used so as to maximize the amount of data that can be collected from each participant. The groups did not show any accuracy or RT differences in the behavioral pilot or the full version of Experiment 2, and were combined at the time of data analysis.

Participants first completed a practice block of trials to ensure that the directions had been understood. The practice block was simply an abridged experimental block, which used different stimuli[8]. After the practice block had been satisfactorily completed, participants began testing with the experimental stimuli. The experiment is most easily conceptualized in terms of blocks composed of a study phase and a test phase. During the study phase of the block participants were shown all four objects from the respective object sets. Two of the objects were labeled as targets and the other two labeled as distracters. Participants were given an unlimited amount of time to study the target objects. When participants indicated via button press that they were ready to continue they were shown a blank screen for 1000 ms to clear any image on the retina. Participants were then shown all 4 objects again in a random order and asked to verify which objects were designated as targets for that particular trial set using the number pad on the keyboard. If participants correctly identified the targets, they continued on to the test phase of the trial set, if not participants were asked to study the set again and continue with the verification process until they could successfully identify the targets.

Next, participants completed the test phase of the block. The test phase began with a fixation cross for 500 ms. Immediately after presentation of the fixation cross, participants were shown one of the four objects from the set presented serially and in random order for 100 ms at a time. If the object shown was designated as a target participants were asked to press the "n" key with the index finger of their right hand as quickly as possible. Conversely, if the object shown was designated as a distracter,

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[8] Practice stimuli consisted of prototype stimuli that were rendered before settling on the current stimulus design. The structural features of these prototype stimuli are similar to those of the experimental stimuli but differ in overall appearance. The prototype stimuli roughly resemble hourglasses.

participants were asked to press the “m” key with the middle finger of the right hand as quickly as possible. Each of the objects appeared for 100 ms with a variable inter-trial interval of 900 – 1200 ms. The test phase of the block consisted of 128 trials. Of these 128 trials, 32 were target trials and 96 were distracter trials (the two targets and two distracters being presented an equal number of times, respectively). Following the completion of all 128 trials, participants once again completed a target verification task, identical to the one described above. However, participants continued on to the next block regardless of their accuracy on the second verification task. The experimental conditions (conjunction, single feature – tapering, or single feature – pinching) were blocked and block order was counterbalanced between participants. Participants completed 15 blocks of 128 trials (5 blocks of each experimental condition). As fatigue can be a major confound in ERP studies, participants were allowed an unspecified length of time to “rest” between blocks and the experiment was resumed when the participant indicated that they were ready to continue. Figure 9 displays a flowchart of Experiment 2 (and the pilot study).

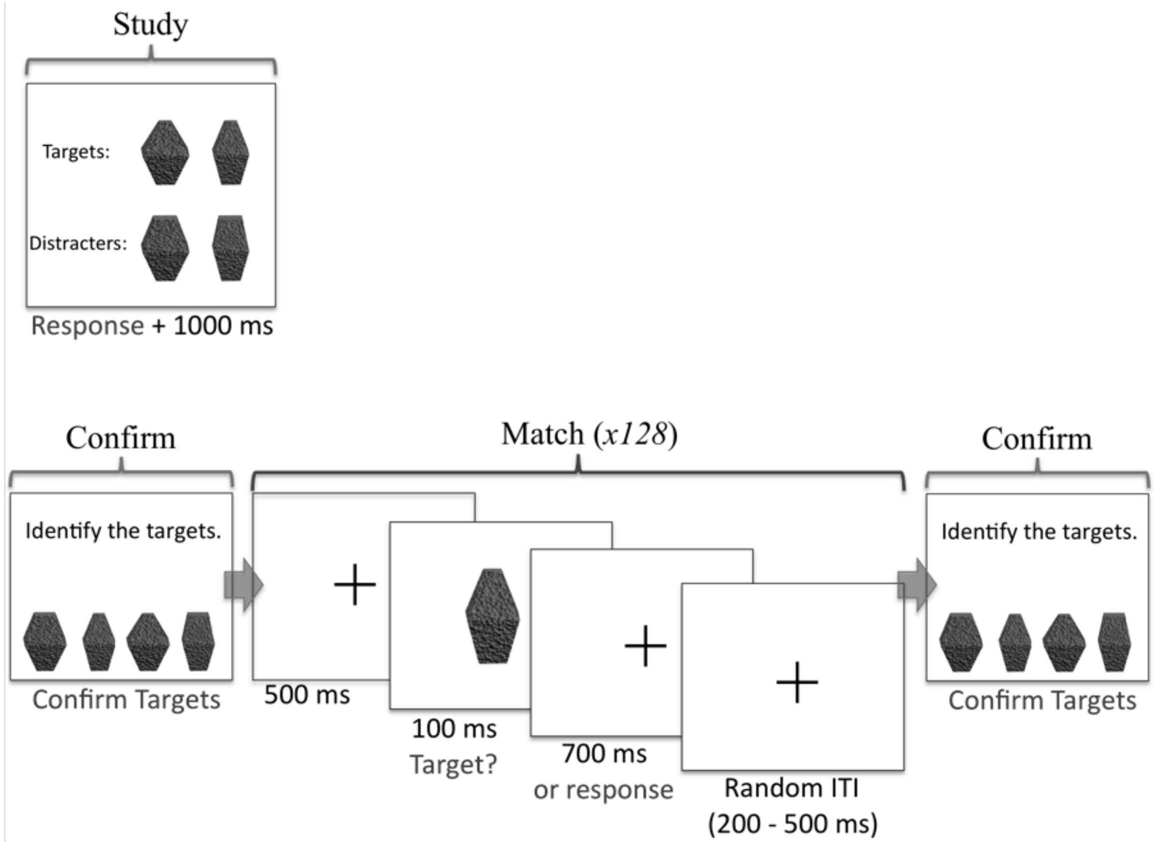

Figure 9. Flowchart of the procedure for Experiment 2 and its pilot study.

Results

Results from the pilot study indicate that the average participant accuracy for the proximal and distal object sets was 82.5% and 88.0%, respectively. As the intent of the pilot study was merely to identify an optimal stimulus set (i.e., within our *a priori* accuracy criteria of 70 – 85%) and not to compare the two object sets in any way, no statistical analyses were conducted.

Discussion

As a result of the findings of our pilot study, the proximal object set (i.e., the inner objects from the previously utilized diamond object set, see Figure 10) was selected as the preferred object set for the full version of Experiment 2 because it fell within our criterion range of 70 – 85% accuracy. The distal object set was discarded, as it was determined too easy to elicit enough participant errors.

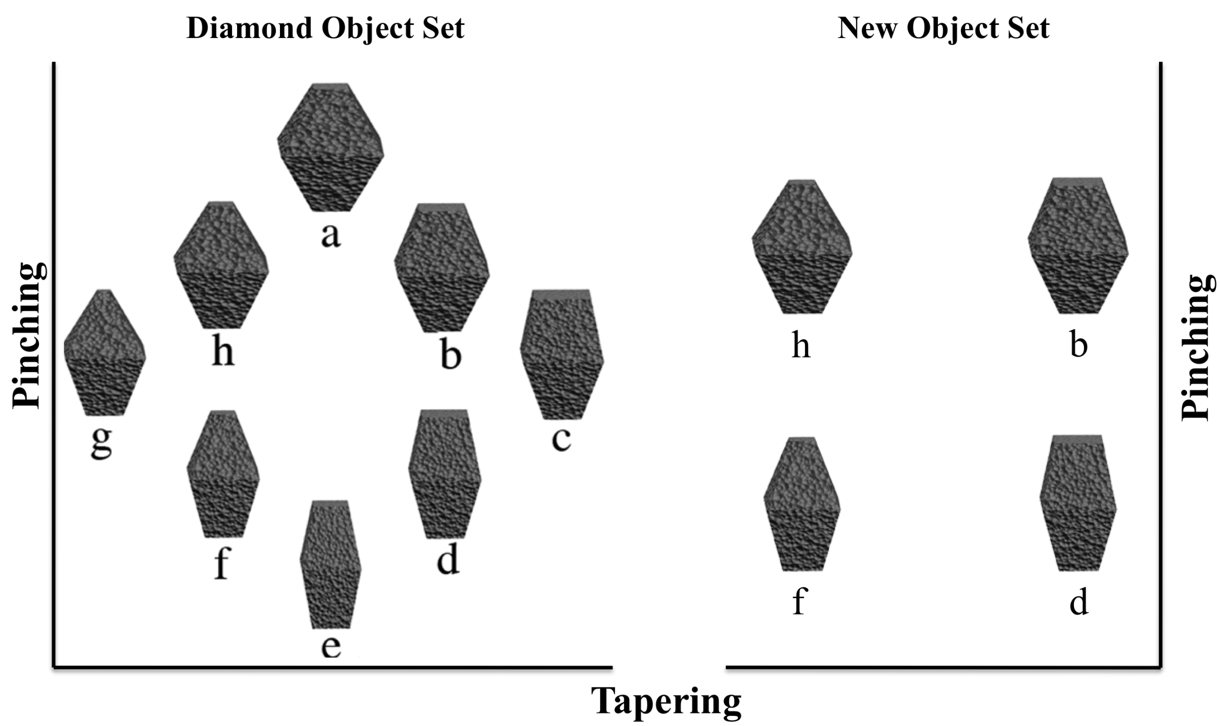

Figure 10. The origin of the four stimuli used in Experiment 2. From the new (proximal) object set both conjunction and single feature sets can be created depending on which two objects are selected as the targets. When the two targets form a line parallel to one of the axes, attention to a single dimension will be sufficient to differentiate targets from distracters (single feature condition). When the two targets form a line diagonal to the axes, structural features must be integrated to distinguish targets and distracters (conjunction condition).

Main Study

As mentioned above, Experiment 2 utilized an ERP paradigm to observe a difference in the time course of early perceptual processing between single feature and conjunction conditions. To do this we used a standard P3-recruitment paradigm, whereby time course differences in object recognition processing are observed as latency differences in the P3 component. While the actual process that the P3 reflects remains a subject of some debate (Luck, 2005), its presence is strong enough and reliable enough to be used as a marker by which time object recognition processes have been completed and thus differences between conditions can be assessed.

Because we intended to primarily investigate perception in this experiment (and not memory), we allowed participants an unlimited amount of time to study the designated targets and distracters at the beginning of each block. To further ensure that participants could readily recall and disambiguate targets and distracters, they were forced to correctly verify the two targets immediately after study before proceeding on to the test portion of the block. In this way, we hoped to ensure that participants had successfully encoded target stimuli before beginning the perceptual task. Further still, if participants failed to correctly verify the targets in the second verification task (after the presentation of the serially presented match/mismatch task) all data from that block was excluded from behavioral analyses (see Discussion).

We anticipated an effect of both response times and sensitivity (*d'*) between the two single feature conditions and a conjunction condition. The necessary recruitment of an integration process during perceptual processing in the conjunction condition should not only increase participant response time but also reduce accuracy (as measured by sensitivity) due to the effect of shared features on object similarity. Electrophysiological data were predicted to show P3 latency differences and N1 magnitude differences between average waveforms from the single feature and conjunction conditions, further indicating the activity of an integration process in the conjunction condition and replicating the findings of Cortese, et al (1999).

Method

Participants. 28 individuals from the University of Richmond community participated in Experiment 2. Of these 28 participants, two were removed from behavioral and electrophysiological analyses as a result of chance performance on the behavioral task (as indicated by a d' value less than 0). As a result, the total number of participants included in behavioral (i.e., *d'* and RT) analyses was 26. An additional four participants were withdrawn from electrophysiological analyses; three because they identified themselves as left-handed[9] and an additional participant whose electrophysiological data was incomplete. The total number of participants included in electrophysiological analysis was 22. All participants were compensated at least $20 for the 2+ hour experiment at a rate of $10/hr. The study was open to all members of the University of Richmond community, 18 or older.

Materials. The proximal object set (i.e., the four inner stimuli from the diamond object set; b, d, f and h) from the pilot study were utilized in Experiment 2 (see Figure 8). Electrophysiological data acquisition and analysis was conducted using Neuroscan SynAmps[2] equipment and Neuroscan SCAN 4.3/4.4 software. Our ERP caps use Quickcells – small sponges that are filled with a saline solution – to retrieve electrical information from the scalp.

Procedure. When participants arrived in the lab they were given a handout on the ERP procedure (see Appendix). Upon reading the handout, the participant was given a chance to ask questions and had the option to opt-out of the experiment if they felt uncomfortable with the procedures. When written consent was received by the

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[9] It is common practice not to include left-handed participants in electrophysiological analyses, as differences in left-handed brain topography can strongly bias the resulting averages of scalp activity collected during testing (Luck, 2005).

experimenter, participants were asked to sit in the testing room while one or two experimenters attached the electrode cap. Once the cap was attached and the connection determined to be good, the experimenters reminded the participant of the nature of the task, left the room, began recording from the cap and the experiment began. The procedures for Experiment 2 are identical to those outlined in the Pilot Study section with the one exception that there was only one object set condition (see Figure 9).

The EEG was recorded using standard electrode locations (International 10/20 System names: F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, P7, P8, PO7, PO8, O1 and O2) for P3 and N1 studies (Cortese, Bernstein, & Alain, 1999; S. J. Luck, 2005; S. J. Luck & Hillyard, 1990; S. J. Luck, 1998; Vogel & Luck, 2000), digitized continuously (1000 Hz sampling rate per channel) using NeuroScan software and archived for offline analysis. The recordings were made through Neuroscan Quickcell electrodes (described above). The HEOG was recorded between the left and right external canthi to monitor any lateral eye motions, and the VEOG was recorded from above and below the left eye to monitor blinking (seeS. J. Luck & Hillyard, 1990). All electrodes were digitally filtered using a lowpass filter set up at 200 Hz during recording and then later subjected to a bandpass filter of 0.1 - 30 Hz offline. Before averaging, ocular and other artifacts were removed using NeuroScan software. Averaging occurred offline for epochs from 200 ms pre-stimulus to 800 ms post-stimulus. The ERPs were referenced to the average of the left and right mastoids after averaging.

Results

Behavioral. Sensitivity (*d'*) values were calculated from each individual's accuracy data in the three test conditions. The one-way within subjects ANOVA for condition was significant $F(2,50) = 54.41$, $p < .001$, partial $\eta^2 = .685$. Further, pairwise comparisons using a Bonferoni adjustment indicated that mean sensitivity for the conjunction condition ($d' = 1.04$) was significantly less than both the single feature - pinching ($d' = 2.49$) and single feature - tapering ($d' = 2.57$) conditions ($p < 0.001$). Sensitivity for tapering and pinching conditions did not differ ($p > 0.05$; see Figure 12).

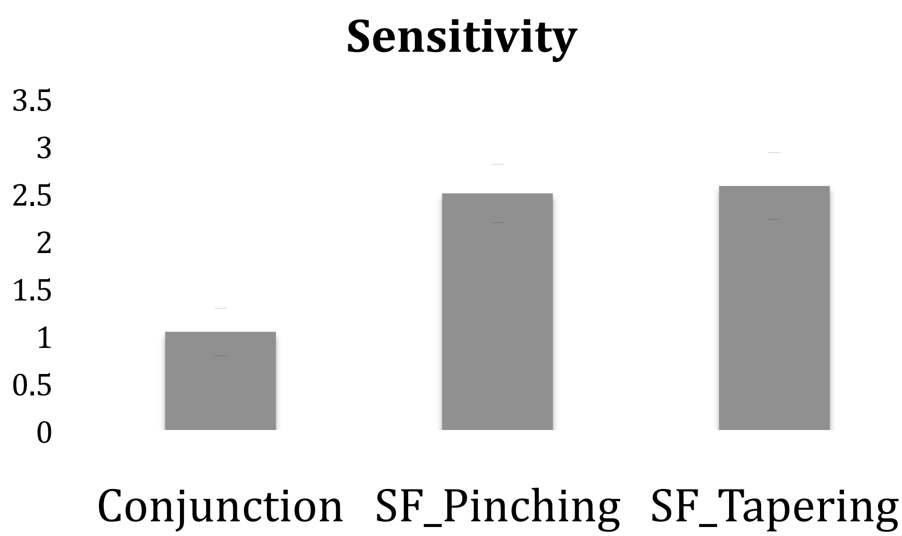

Figure 12. Sensitivity values for each of the three conditions. Error bars represent 95% confidence intervals.

The one-way within subjects ANOVA of RT data was also significant ($F(2,50) = 107.81$, $p < .001$, partial $\eta^2 = .812$) and pairwise comparisons using a Bonferoni adjustment indicated that mean response time for the conjunction condition ($M = 563$) was significantly higher than both the single feature - pinching ($M = 455$) and single feature - tapering ($M = 448$) conditions ($p < 0.001$), which did not differ from one another ($p > 0.05$; see Figure 13)

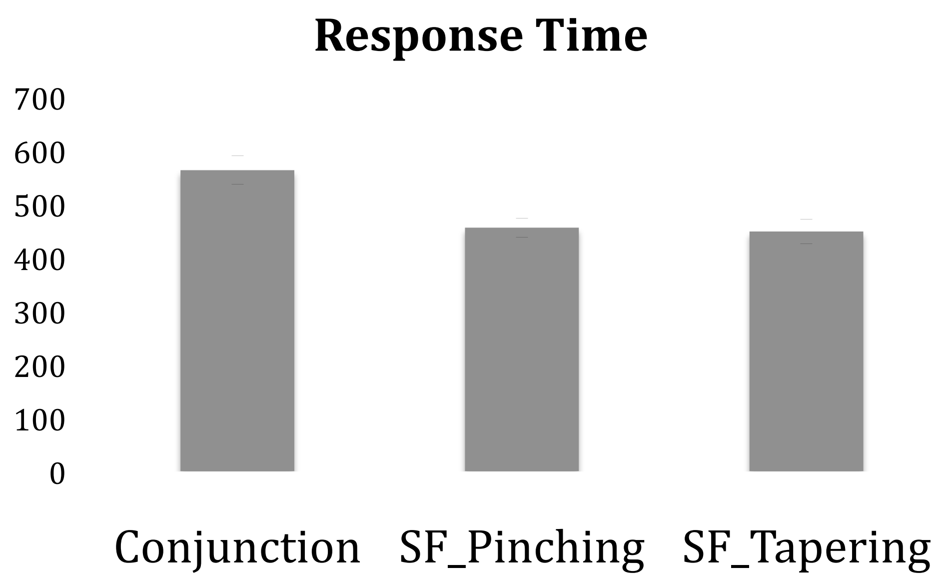

Figure 13. Response times for each of the three experimental conditions. Error bars represent 95% confidence intervals.

Electrophysiological Data – the P3. Only correct trials (i.e., "hits" for target trials and "correct rejections" for distracter trials) were utilized in analysis of P3 data. For each participant, average distracter waves in each condition were subtracted from average target waves (see Figure 14). For each of the resultant difference wave forms, the peak latency of the P3 was calculated by finding the local maximum between 400 and 700 ms. P3 latency data from the 9 electrodes of interest (F3, Fz, F4, C3, Cz, C4, P3, Pz and P4) was submitted to a 3 x 3 x 3 ANOVA with condition (conjunction, single feature – tapering and single feature – pinching) anterior-posterior position (frontal, central and parietal) and left-right position (left, midline and right) as input variables. The overall 3 x 3 x 3 ANOVA revealed a significant main effect for condition ($F(2,42) = 124.58$, $p < 0.001$), anterior-posterior position ($F(2,42) = 31.11$, $p < 0.001$) and left-right position ($F(2,42) = 8.24$, $p = 0.001$). Further, significant 2-way interactions were found for condition x anterior-posterior position ($F(4,84) = 3.14$, $p < 0.05$) and anterior-posterior position x left-right position ($F(4,84) = 5.93$, $p < 0.001$) and the 3-way interaction was significant as well ($F(8,168) = 3.14$, $p < 0.05$).

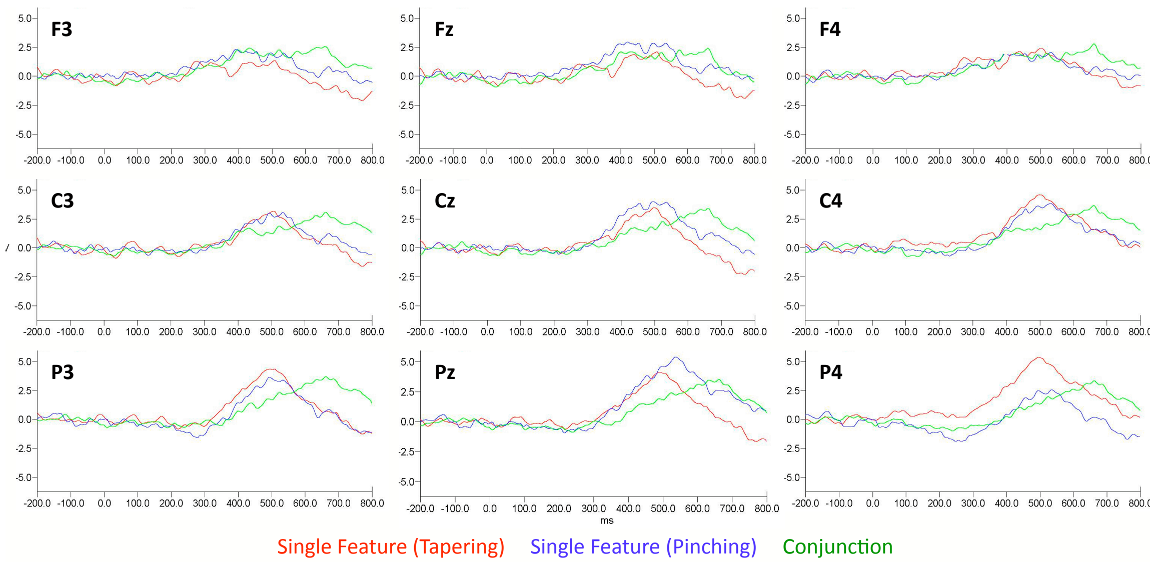

Figure 14. Difference waves from each of the three experimental conditions overlapped for each of the nine electrodes of interest.

As there was no 2-way interaction of condition x left-right position, data were collapsed across this (left-right) factor. Three separate one-way, within-subjects ANOVAs were conducted to test the anterior-posterior positions (frontal, central and parietal) separately by condition. Using a Bonferroni adjustment α was set at 0.017. The ANOVA for the central electrode sites was found to be significant ($F(2,42) = 35.68$, $p < 0.001$), as were the ANOVAs for frontal sites ($F(1.54,32.25) = 54.44$, $p < 0.001$) and parietal sites ($F(1.53,32.16) = 28.18$, $p < 0.001$), which were accompanied by the Greenhouse-Geisser epsilon correction for nonsphericity. For both the frontal and parietal sites Tukey post-hoc comparisons of the three conditions indicated that the mean peak latencies of the P3 in conjunction condition (*M*s = 632 and 616, respectively) was greater than in both the single feature – tapering (*M*s = 514 and 545) and single feature –

pinching (*M*s = 526 and 526) conditions ($p < 0.05$), which did not differ ($p > 0.05$). For the central sites Tukey post-hoc comparisons of the three conditions indicated that the mean peak latency of the P3 was significantly different in all three conditions ($p < 0.05$); however, mean latency in the conjunction condition ($M = 562$) was notably larger than in both the single feature –tapering ($M = 500$) and single feature – pinching ($M = 471$) conditions (see Figure 15).

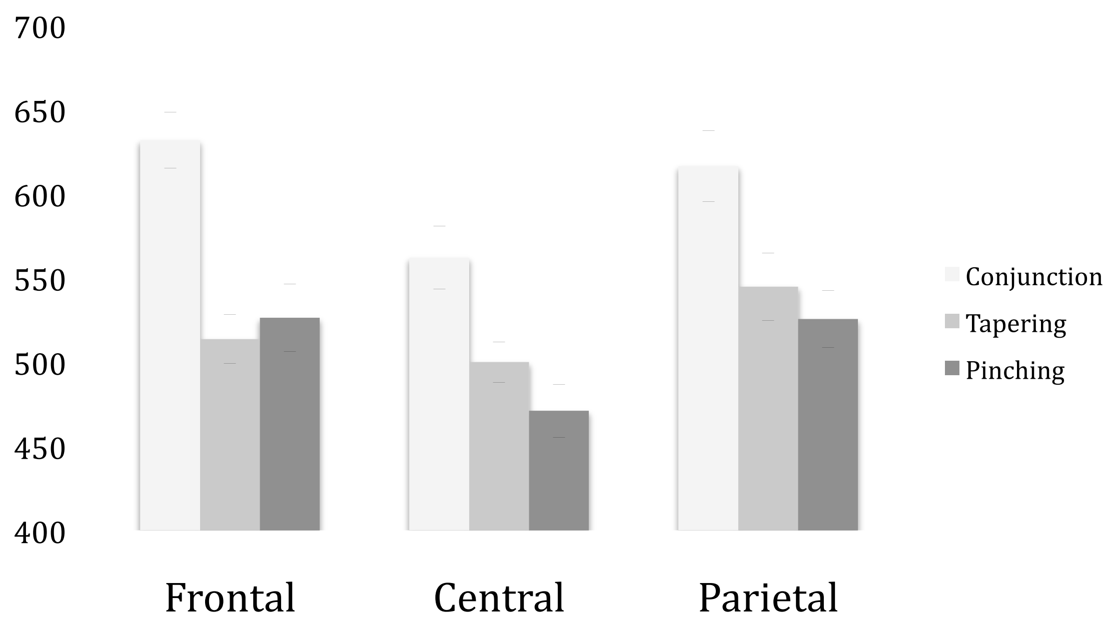

Figure 15. P3 peak latency values (ms) for the three experimental conditions x the three anterior-posterior electrode positions. Error bars represent 95% confidence intervals.

Electrophysiological Data – the N1. Only correct target trials (i.e., "hits") were utilized in the analysis of N1 data. Both peak latencies and mean amplitudes of the N1 within the window of 160 – 220 ms were calculated for the electrodes of interest (P7, P8, PO7, PO8, O1 and O2; see Figure 16). Two separate 3 x 2 x 3 ANOVAs were conducted for peak latency and mean amplitude data with condition, anterior-posterior position (parietal, parietal-occipital and occipital) and left-right position (left and right) as input variables. The peak latency ANOVA indicated a main effect of both condition ($F(2,42) =$

14.51, $p < 0.001$) and anterior-posterior position ($F(2,42) = 6.86$, $p < 0.01$). Tukey's post-hoc comparisons revealed that all three conditions were significantly different from one another as were all three anterior-posterior positions ($p < 0.05$; see Figure 17). The mean amplitude ANOVA indicated only a significant interaction of condition and anterior-posterior position ($F(4,84) = 0.97$, $p < 0.05$), which was the result of a dissociation between the conjunction and single feature –tapering conditions at posterior-occipital and occipital positions (see Figure 18).

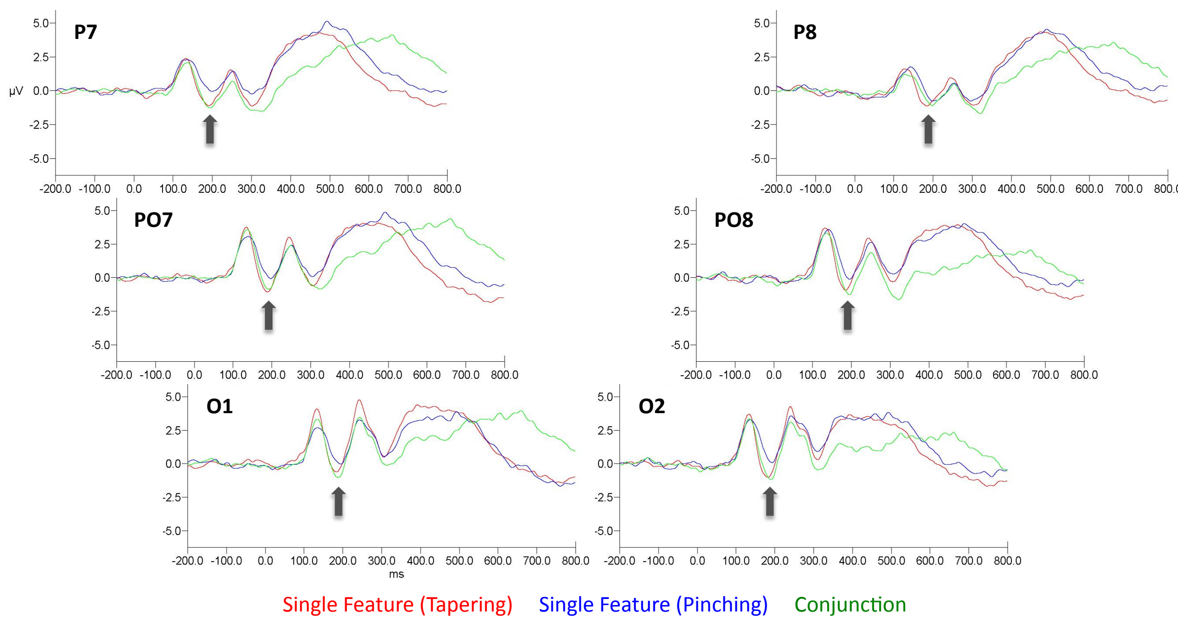

Figure 16. Target trial waves for each of the three experimental conditions overlapped for each of the six electrodes of interest. Arrows indicate the N1 component.

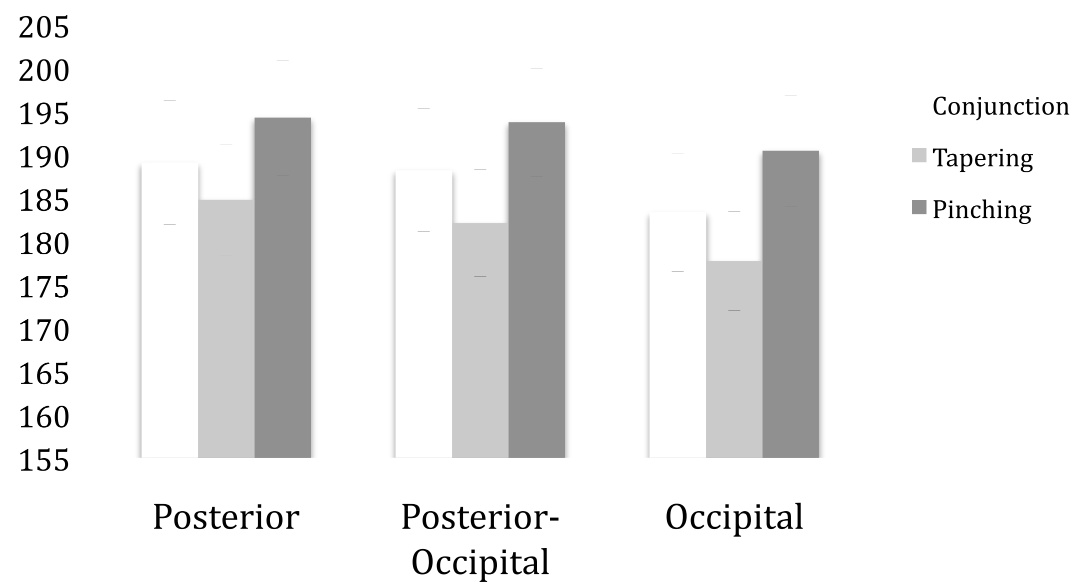

Figure 17. N1 peak latencies (ms) for the three test conditions by the three anterior-posterior electrode positions. Error bars represent 95% confidence intervals.

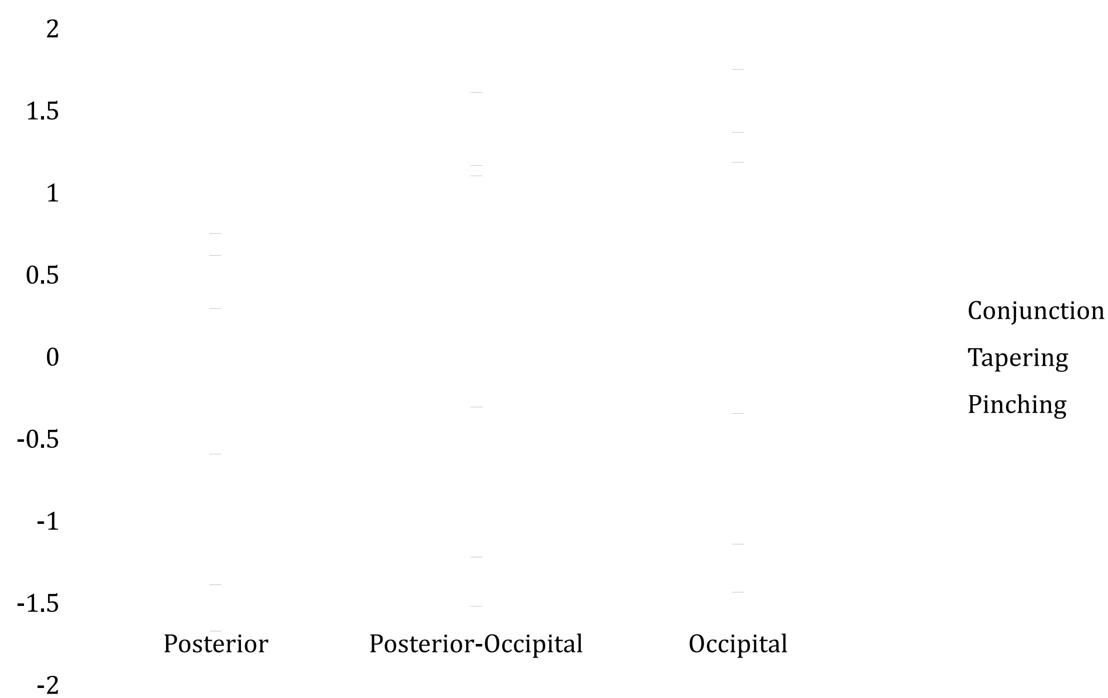

Figure 18. N1 mean amplitude (μV) for the three test conditions by the three anterior-posterior electrode positions. Error bars represent 95% confidence intervals.

Discussion

Behavioral results from Experiment 2 indicate that participants were slower and less accurate in their responses in the conjunction condition than in either of the single feature conditions. These findings were corroborated by electrophysiological data, which indicated that the P3 latency for conjunction conditions was consistently larger than for either of the single feature conditions (see Figure 14). We propose that these differences are evidence supporting the existence of a structural feature integration process that must be activated before the conjunction task can be successfully completed. Thus, tasks that require integration (conjunction condition) should take longer to complete than those that do not (single feature conditions) reflecting the extra time required to integrate features (as evidenced by our RT and electrophysiological data). Further, as an additional process must take place for tasks that require integration, the risk of error should be greater for these trials (as evidenced by our sensitivity data). As the exact same four stimuli were used in each condition, the difficulty participants experienced in the conjunction condition cannot be attributed to the stimuli themselves, but rather, must be attributed to the integration process.

Further, we find that differences in the mean amplitude and peak latency of the lateralized occipital N1 subcomponent do not reflect an integration process or a difference between single feature and conjunction conditions. That is, the single feature – pinching condition exhibited the greatest magnitude and the greatest latency in the N1 component of the three conditions, followed by the conjunction condition and lastly the single feature – tapering condition (see Figure 16). There was no systematic variance of the N1 component between the conjunction condition and the single feature conditions as there would have to be for the differences in N1 shape to reflect integration. Instead it is more likely that the differences in N1 reported in this study simply reflect differences in difficulty of discrimination at the single feature level (i.e., prior to integration), which is supported by other literature on the lateralized occipital subcomponent of the N1 (S. J. Luck, 2005). For example, when attended to singly, discriminations for the pinching dimension were more difficult than for the tapering dimension (see the stimulus manipulation check in Experiment 1). Thus, between the two single feature conditions, it should be expected that trials that require the discrimination of pinching values would be more difficult. The increased latency and amplitude of the N1 in the single feature – pinching condition is most likely a direct reflection of this effect. That the latency and amplitude of the conjunction condition falls somewhere between the two single feature conditions is probably the result of single feature processing at this stage in perception. Thus, if participants attended to pinching first in half of the trials and tapering first in the other half of the trials, and average of these trial waves would result in something about half way between the two single feature conditions. If this is the case, it provides further evidence that the differences in the N1 (160 – 220 ms post stimulus) are merely the result of single feature discriminations and precede the integration process.

These results may at first seem to refute those of Cortese, et al. (1999) as we have shown that the N1 cannot be a marker of an integration process. However, it must be noted that Cortese, et al. utilized completely different features and focused their ERP analyses on an anterior sites. It could be then that Cortese, et al. examined a separate subcomponent of the N1 (one that is more anterior) than did we. Perhaps, Cortese, et al.'s results represent some kind of decisional processes that overlap with the discriminating processes evidenced by the lateralized occipital N1 subcomponent and are thus involved in an integration process, but without further study it is difficult to say.

One limitation of this study is its inability to completely rule out the effect of integration in memory. That is, in the conjunction trials of Experiment 2 participants had to not only integrate the structural features of an object at perception, but also integrate the structural features of the object when retrieving the target object from memory (see Experiments 1b and 1c). While we are unable to completely rule out the possibility that integration during recall partially or completely accounted for our results, this possibility is highly unlikely for a number of reasons. First, we required participants to verify the two targets before beginning the match/mismatch portion of the experiment. Thus, we ensured that participants had adequately encoded the target stimuli during the study phase and were capable of successfully recalling them. It should also be noted that participants completed this first verification task with minimal difficulty – suggesting that a very minimal burden was placed on memory. Second, our task put an enormous strain on perception as participants had only 100 ms to view an object before having to make a target/distracter distinction. Thus, while the burden placed on memory was minimal, the burden placed on perception was quite large. Further, unlike the verification task, participants experienced significant difficulty with the match/mis-match task, suggesting that the majority of participants' errors were the result of errors in integration during perception (not memory). Third, given the constraints of the experiment, it is unlikely that participants recalled the target objects from memory with each trial, but rather were able to hold the object in working memory for the duration of the block.

It should be noted that behavioral and electrophysiological data cannot be directly compared for these analyses as the number of participants differed and blocks in which participants misidentified targets in the second verification task were removed from the behavioral analyses but not electrophysiological analyses. An oversight in data coding made the removal of such blocks from electrophysiological data prohibitive. However, correct trials from blocks where the participants failed to correctly verify the targets in the second verification task represented only about 8% of trials. Furthermore, of this 8% of trials more than half showed high accuracy values, making inadequate coding of the targets unlikely and suggesting that participants merely made a mistake on the second verification task. Regardless, the variance that these few possible error trials might have introduced into the electrophysiological data could only have served to make our data less significant and are considered a negligible source of error variance.

GENERAL DISCUSSION

We set out to assess the effect of shared features on perceptions of object similarity across three domains: perception, working-memory and long-term recall. Furthermore, to control for the effect of proximity we equated our stimuli for physical inter-object distance. It has been suggested that object features are represented in a distributed fashion and that these distributed features must be integrated not only during recall but also at the time of perception (Kruschke, 1992; Treisman & Gelade, 1980). If this model is correct, shared features should increase object similarity by increasing the demand on an integration mechanism. Further, we have proposed that similarity cannot be measured by pairwise comparisons, as similarity will be partially determined by the properties of the entire object set. As such, we devised all of our studies to test setwise similarity. We expected to find that shared features do indeed help determine object similarity insofar as they recruit and tax a feature integration mechanism. Our predictions were largely born out by our results, which suggest that much like CSVA patient ELM, normal observers show a larger number of object confusions for objects that share structural features in tasks of memory. Specifically, when tested in a working memory (Experiment 1b) and a long-term recall (Experiment 1c) task, performance with the square object set was significantly worse than for the diamond object set. This difficulty was not observed in a perceptually demanding task (Experiment 1a), however this may have been because participants had an unlimited amount of time to respond.

Further, follow-up chi-squared analyses for Experiment 1 revealed that for the memory tasks a disproportionate number of participant confusions were exhibited between object pairs with a shared diagnostic feature (i.e., a parallel relationship). Thus, the poorer performance of participants assigned to the square object set (more shared features relative to the diamond object set), implies an effect of shared features during recall. In terms of a dynamic model of object recognition, these results suggest an impoverished representation of object dimensions when structural information is integrated at recall. That is, the poor resolution or complete absence of diagnostic structural information during integration drove object confusions at recall. Interestingly this effect was only seen in tasks of memory (Experiment 1b and 1c). Assuming that integration must take place during perception (i.e., the forming of a percept) as well as during recall, an effect should also be present in a perceptually demanding task. For this reason, Experiment 2 was conducted to test for the presence of an integration process during perception (see below). It could be that our perceptual manipulation in Experiment 1a was not strong enough to see an integration effect in perception, but at the very least, it shows that these errors are more likely to occur during a task that taps memory.

The results presented above suggest that our stimuli were stored as distributed representations of *sub-geon* features (i.e., pinching and tapering); however, these results do not stand in opposition to models such RBC and JIM.3 that utilize stored geon information. That is, although we find support for a sub-geon model of object recognition (which Hummel and Biederman allow for in their models) we have found no evidence to suggest that geon-type object recognition is not feasible. The structural description component of RBC and JIM.3 can not account for our results, but allowances are made for sub-geon type recognition in the models and we do not seek to refute geon-type object recognition theories. According to models such as RBC and JIM.3, objects may be perceived in terms of their most basic, sub-geon features (i.e., vertices and axes, see Hummel, 2001). We find that at recall (both from working and from long-term memory) as well our stimuli were recalled in terms of separate, sub-geon object features (pinching and tapering) that had to be integrated in order to be properly identified as evidenced by participants' difficulty with shared features. This finding leads us to believe that while storage of geon-like representations are common, certain tasks (especially those involving novel objects) will require the recruitment of the most basic forms of distributed representations of features.

Also in line with object recognition models such as RBC and JIM.3 is the integration of sub-geon features during perception. There must be a feature integration process during perception if shared features are to have any effect on perceived similarity. That no effect of shared features was found in Experiment 1a does not necessarily imply that feature integration does not take place during perception, but merely indicates that our paradigm may not have been sensitive enough to detect the role of shared features during perception. The task in Experiment 1a does not appear to have been too easy (accuracy was not at ceiling), but it may simply be that any difficulty in the task was the result of resolving physical proximity and that this effect was strong enough to completely mask any effect of shared features. This becomes an even more likely possibility if one considers that the role of shared features (i.e., the importance of integration in determining similarity) may be minor relative to physical proximity at perception (see regression results from Experiment 1a). To test whether integration was actually taking place during perception Experiment 2 was conducted.

Experiment 2 provided a more sensitive measure of perceptual integration, not only because it employed electrophysiological technology but also because it put a high (temporal) strain on perception. Thus, unlike Experiment 1a in which participants had an unlimited amount of time to respond, in Experiment 2 participants had only 800 ms to respond. In the single feature conditions, participants only needed to attend to a single structural feature to identify a target; however, in the conjunction condition participants were forced to attend to both tapering and pinching values and integrate them in order to make a target/non-target judgment. In this way, Experiment 2 was designed to detect any differences that might occur (both behaviorally and electrophysiologically) between single feature object identification and multiple feature object identification. The behavioral data from Experiment 2 show a markedly poorer performance of the conjunction condition relative to single feature conditions. Further, even when only correct trials are considered, participants took longer to respond to conjunction trials than single feature trials. As the only difference between conjunction and single feature trials is the need to integrate structural features, these behavioral data strongly suggest that there is an integration process at work during perception, which not only increases the time necessary to perceive and respond to targets that require feature integration but also makes errors more likely when feature integration is necessary. Moreover still, electrophysiological data support these behavioral data while providing an even more sensitive measure of cognitive timing. That is, the increased latency of the P3 in conjunction conditions by about 100-150 ms relative to single feature conditions suggests that there is indeed an additional process that takes place during trials that require integration – likely an integration process. However, this study finds that the early difference in the lateralized occipital N1 subcomponent (~180 ms) between single feature and conjunction condition (likely different than the N1 component detected by Cortese, et al., 1999, see above) cannot be the result of an integration process and likely precedes such a process. Instead, this difference most likely reflects the varying difficulty of perceptual discrimination between our structural features.

Nonetheless, the results from Experiment 2 provide strong evidence that integration does in fact take place during perception, replicating the findings of a number of other similar studies (Arguin & Saumier, 2000; Cortese et al., 1999; Paz-Caballero & García-Austt, 1992; Quinlan, 2003), though this has not been shown with structural features alone in previous work. Thus, taken together, the results of Experiments 1b, 1c and 2 suggest that integration of structural features is necessary during perception, working memory and long-term memory tasks. If integration of structural features is necessary in identifying and distinguishing between objects, than shared features should effect perceived object similarity such that the more features two objects share the more features of those objects will need to be successfully integrated to resolve confusions between the objects. This hypothesis is strengthened by the results of Experiments 1b and 1c, which indicate that indeed, shared features contribute significantly to object confusions. In Experiment 1a, no effect of shared features was observed at all, but sensitivity data from Experiment 2 show that there is indeed an effect of shared features on perceived similarity. While these may seem like contradictory findings, the paradigm in Experiment 2 put far more stress on the perceptual system than did Experiment 1a. Regardless, it can be assumed that the effect of shared features on similarity at perception is fairly weak. Thus, not only do shared features play a role in judgments of object similarity (as measured by object confusions) this effect is largely task-dependent and varies across tasks of perception, working memory and long-term memory.

This task-dependent role of shared structural features on object similarity supports a dynamic model of object representations (Barsalou, 1982; Kruschke, 1992; Treisman & Gelade, 1980) and helps to explain the pattern of deficits observed in ELM (Arguin, Bub, & Dudek, 1996; Dixon, Bub, & Arguin, 1997). That is, ELM exhibited trouble with structural features in tasks of working and long-term memory but not perception (see above). Our results suggest that shared features contribute to object confusions in perception only slightly (relative to physical proximity, see regression data from Experiment 1a). That is to say, if shared features only contribute minimally to similarity at perception, than integration (which is necessary for resolving confusions caused by shared features but not high physical object proximity and precisely what is proposed to account for ELM's difficulties) in turn should also have a minimal role in resolving confusions during perception. This would explain ELM's lack of difficulty in a perceptual task (as well as our participants' from Experiment 1a).

It is important to note that these results cannot be completely accounted for by the structural descriptions component of model's such as RBC and JIM.3, which may suggest that structural information is stored as reducible, complex shape primitives (i.e., geons). Indeed, our stimuli could almost certainly be conceived of as geons, in which case no features should need be integrated during recall. The object would merely represent itself in a distributed model. Instead, we find that our stimuli must be conceptualized in terms of their more primitive, sub-geon features (i.e., tapering and pinching) in order to understand our results and how an integration mechanism works. Specifically, objects are not composed of geons alone, but less complex elements that make-up geons and, in turn, objects. Indeed these finding support the non-structural descriptions components of RBC and JIM.3 and expand the evidence for sub-geon visual recognition mechanisms.

Lastly, we do not wish to imply that shared features are the single determinant of similarity, nor that they are the most important. Physical proximity seems capable of accounting for far more of the difficulty that individuals show when resolving object confusions. Furthermore, other factors not discussed in this paper certainly effect similarity to an equal or greater extent than shared features, including factors from other domains such as conceptual information (see Kinka, D., Roberts, K. & Bukach, C. M. manuscript in prep). However, in testing the role of shared features we have in turn tested both a Feature Integration Theory (Treisman & Gelade, 1980) as well as a dynamic model of object processing (Barsalou, 1982; Kruschke, 1992) and found support for each. Most importantly, we have demonstrated that pairwise measures of similarity are inadequate, as they fail to account for the properties of the set (such as shared features) on perceived similarity. We suggest that in the future studies of similarity account for these setwise influences on similarity and acknowledge that similarity is best conceived of in terms of a dynamic model of distributed (sometimes sub-geon) features.

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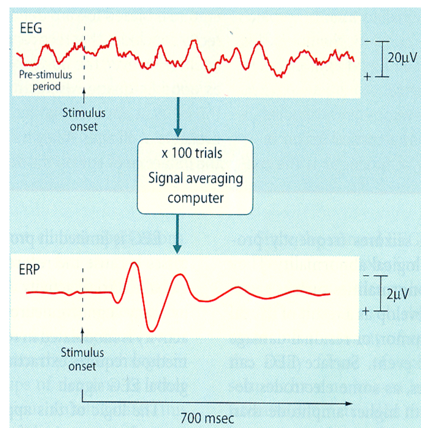
APPENDIX

ERP Handout
What is EEG?

Electrical activity of active brain cells produces currents spreading through the head. These currents reach the scalp surface, and resulting voltage differences on the scalp is recorded as the electroencephalogram (EEG).
EEG is a *continuous* recording of fluctuating voltages and reflects different *brain states* (sleep, arousal, abnormal states)

What is ERP?

Event-related potentials (ERP) *averages* small portions of the EEG activity in response to particular events, such as the presentation of a picture or sound, or the demands of a particular task.
The averaged ERP wave is made up of a series of bumps called *components* that reflect the time course of specific mental processes that occur as your brain responds to the picture, sound, or task.



What to expect.

During an ERP experiment, you will wear a cap, similar to a swim cap, that contains 64 sensors. The equipment is safe and is used commonly in psychology experiments. The sensors are small cylindrical sponges with a flat metal surface that rests against your scalp. The sponges are injected with a saline solution (primarily water and salt) to help with electrical conductance. The sensors in the cap only measure the activity; they do not stimulate the neurons. Because hair products and oils can interfere with the electrical signal, we ask that you **wash your hair with shampoo only** (do not use conditioner) and **do not use any other hair products** such as gels or hair spray on the day that you are tested.

In addition to the sensors on the cap, there are a couple of sensors that are placed on your ears, and just above or below one eye (to help us tell when you blink or move your eyes). We ask that you **do not wear any makeup** (or remove the makeup) as the makeup will interfere with the skin conductance. The skin in the centre of each sensor is first cleaned and degreased with a cotton bud dipped in alcohol and then gently rubbed with a cotton bud dipped in a chlorided, slightly abrasive, electrolyte gel. The purpose of this is to lower the impedance of the skin so that the electrical signal is conducted better. Great care is taken not to damage the skin, and you are encouraged to tell us if this rubbing action is uncomfortable. If so, it is stopped and not repeated. This whole procedure of placing the cap and supplementary electrodes may take between 15 and 30 minutes. We will give you magazines and refreshments while we do these preparations.

Once the cap is ready, you will sit by yourself in a quiet room and complete the experiment. An experiment typically involves pressing a button or making a verbal reply in response to a picture or sound presented on the computer. Participants are instructed on the particular task and about how long the experiment will take. The experiments will be in the adjoining room. You will be monitored at all times by cameras placed in the room, and you can communicate freely through the intercom if you need to speak to the experimenter. It will be very important that you stay as still as possible during the tasks, as any movements will interfere with the electrical signal. This includes movement from eye blinks and swallowing. We ask that you try to minimize eye blinks and swallows during the presentation of a picture, and use the time between trials to blink or swallow. We also ask that you do not chew gum. You are encouraged to take a break whenever needed. Refreshments will be provided.

On completion of the experiment, we will remove the cap and all electrodes. Your hair may be a bit damp or flattened as a result of the cap. If you would like to wash or style your hair afterwards, we have a sink with a sprayer and will provide clean towels, shampoo, conditioner, and a hair dryer. We ask that you bring your own brush. You may also reapply your makeup at this time.

Equipment cleaning and maintenance

The caps are disinfected in alcohol after every experimental session. Towels are used only once by a participant and then washed.

EEG/ERP involves recording (not stimulation), so is completely harmless.

REFERENCES

Arguin, M., & Saumier, D. (2000). Conjunction and linear non-separability effects in visual shape encoding. Vision Research, 40(22), 3099-3115. doi:10.1016/S0042-6989(00)00155-3

Arguin, M., Bub, D., & Dudek, G. (1996). Shape integration for visual object recognition and its implication in category-specific visual agnosia. Visual Cognition, 3(3), 221-275. doi:10.1080/713756740

Barsalou, L. W. (1982). Context-independent and context-dependent information in concepts. Memory & Cognition, 10(1), 82-93.

Biederman, I. (1987). Recognition-by-components: A theory of human image understanding. Psychological Review, 94(2), 115-147. doi:10.1037/0033-295X.94.2.115

Blais, C., Arguin, M., & Marleau, I. (2009). Orientation invariance in visual shape perception. Journal of Vision, 9(2), 14.1-23.

Bukach, C. M. (2004). Category specificity in normal recall: Investigations of the verbal and visual domain. ProQuest Information & Learning). Dissertation Abstracts International: Section B: The Sciences and Engineering, 65(4), 2082-2082. . (2004-99020-307)

Bukach, C. M., Bub, D. N., Masson, M. E. J., & Lindsay, D. S. (2004). Category specificity in normal episodic learning: Applications to object recognition and category-specific agnosia. Cognitive Psychology, 48(1), 1-46. doi:10.1016/S0010-0285(03)00100-2

Cortese, F., Bernstein, L. J., & Alain, C. (1999). Binding visual features during high-rate serial presentation. Neuroreport, 10(7), 1565-1570.

Czerwinski, M., Lightfoot, N., & Shiffrin, R. M. (1992). Automatization and training in visual search. The American Journal of Psychology, 105(2), 271-315.

Dixon, M., Bub, D. N., & Arguin, M. (1997). The interaction of object form and object meaning in the identification performance of a patient with category-specific visual agnosia. Cognitive Neuropsychology, 14(8), 1085-1130. doi:10.1080/026432997381286

Dunn, J. C. (1983). Spatial metrics of integral and separable dimensions. Journal of Experimental Psychology: Human Perception and Performance, 9(2), 242-257. doi:10.1037/0096-1523.9.2.242

Durbin, J., & Watson, G. S. (1951). Testing for serial correlation in least squares regression. II. Biometrika, 38(1-2), 159-178.

Edelman, S., & Intrator, N. (2003a). Towards structural systematicity in distributed, statically bound visual representations. Cognitive Science, 27, 73-109.

Edelman, S., & Intrator, N. (2003b). Better limited systematicity in hand than structural descriptions in the bush: A reply to Hummel. Cognitive Science, 27, 331-332.

Farah, M. (1992). Is an object an object an object: Cognitive and neuropsychological investigations of domain-specificity in visual object recognition. Current Directions in Psychological Science, 1, 164–169.

Feldman, J., & Richards, W. (1998). Mapping the mental space of rectangles. Perception, 27(10), 1191-1202. doi:10.1068/p271191

Field, A. (2009). Discovering statistics using SPSS (and sex and drugs and rock 'n' roll) (third ed.). Los Angeles, California: SAGE Publications.

Goldstone, R. L. (1998). Perceptual learning. Annual Review of Psychology, 49, 585-612. doi:10.1146/annurev.psych.49.1.585

Goldstone, R. L. (2000). Unitization during category learning. Journal of Experimental Psychology.Human Perception and Performance, 26(1), 86-112.

Grossberg, S. (1984). Unitization, automaticity, temporal order, and word recognition. Cognition & Brain Theory, 7(3), 263-283.

Hummel, J.E., & Biederman, I. (1992). Dynamic binding in a neural network for shape recognition. Psychological Review, 99, 480–517.

Hummel, J.E., & Stankiewicz, B.J. (1996). An architecture for rapid, hierarchical structural description. In T. Inui & J. McClelland (Eds.), Attention and performance MA: MIT Press.

Hummel, J.E., & Stankiewicz, B.J. (1998). Two roles for attention in shape perception: A structural description model of visual scrutiny. Visual Cognition, 5, 49–79.

Hummel, J. E. (2001). Complementary solutions to the binding problem in vision: Implications for shape perception and object recognition. Visual Cognition, 8, 489–517.

Hummel, J. E. (2003). “Effective systematicity” in, “effective systematicity” out: a reply to Edelman and Intrator (2003). Cognitive Science, 27, 327-329.

Humphreys, G. W., & Forde, E. M. E. (2001). Hierarchies, similarity, and interactivity in object recognition: 'category-specific' neuropsychological deficits. Behavioral and Brain Sciences, 24(3), 453-509.

Humphreys, G. W., Riddoch, M. J., & Quinlan, P. T. (1988). Cascade processes in picture identification. Cognitive Neuropsychology, 5(1), 67-104. doi:10.1080/02643298808252927

Johnson, R. (1986). A triarchic model of P300 amplitude. Psychophysiology, 23(4), 367-384. doi:10.1111/j.1469-8986.1986.tb00649.x

Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. Psychological Review, 99(1), 22-44. doi:10.1037/0033-295X.99.1.22

Kutas, M., McCarthy, G., & Donchin, E. (1977). Augmenting mental chronometry: The P300 as a measure of stimulus evaluation time. Science, 197(4305), 792-795.

Laws, K. R., Gale, T. M., Frank, R., & Davey, N. (2002). Visual similarity is greater for line drawings of nonliving than living things: The importance of musical instruments and body parts. Brain and Cognition, 48(2), 421-424.

Luck, S. J. (1998). Sources of dual-task interference: Evidence from human electrophysiology. Psychological Science, 9(3), 223-227. doi:10.1111/1467-9280.00043

Luck, S. J. (2005). In Gazzaniga M. S. (Ed.), An introduction to the event-related potential technique. Cambridge, Massachusetts: The MIT Press.

Luck, S. J., & Hillyard, S. A. (1990). Electrophysiological evidence for parallel and serial processing during visual search. Perception & Psychophysics, 48(6), 603-617.

Magliero, A., Bashore, T. R., Coles, M. G., & Donchin, E. (1984). On the dependence of P300 latency on stimulus evaluation processes. Psychophysiology, 21(2), 171-186. doi:10.1111/j.1469-8986.1984.tb00201.x

Mate, J., & Baqués, J. (2009). Visual similarity at encoding and retrieval in an item recognition task. Quarterly Journal of Experimental Psychology (2006), 62(7), 1277-1284.

Palmer, S. E. (1999). A.3 difference thresholds. Vision science: Photons to phenomenology (pp. 671-672). Cambridge, Massachusetts: The MIT Press.

Paz-Caballero, M., & García-Austt, E. (1992). ERP components related to stimulus selection processes. Electroencephalography & Clinical Neurophysiology, 82(5), 369-376. doi:10.1016/0013-4694(92)90006-4

Quinlan, P. T. (2003). Visual feature integration theory: Past, present, and future. Psychological Bulletin, 129(5), 643-673. doi:10.1037/0033-2909.129.5.643

Schyns, P. G., & Rodet, L. (1997). Categorization creates functional features. Journal of Experimental Psychology: Learning, Memory, and Cognition, 23(3), 681-696. doi:10.1037/0278-7393.23.3.681

Schyns, P. G., Goldstone, R. L., & Thibaut, J. (1998). The development of features in object concepts. Behavioral and Brain Sciences, 21(1), 1-54. doi:10.1017/S0140525X98000107

Snodgrass, J. G., & Vanderwart, M. (1980). A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity. Journal of Experimental Psychology: Human Learning and Memory, 6(2), 174-215. doi:10.1037/0278-7393.6.2.174

Tanaka, J. W., & Farah, M. J. (1993). Parts and wholes in face recognition. Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 146A, 225–245.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. Cognitive Psychology, 12(1), 97-136. doi:10.1016/0010-0285(80)90005-5

Vogel, E. K., & Luck, S. J. (2000). The visual N1 component as an index of a discrimination process. Psychophysiology, 37(2), 190-203. doi:10.1017/S0048577200981265

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Curriculum Vitae

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Honors Thesis: Effects of Adult Treatment with Nicotine and the Antidepressant Fluoxetine on Male Rats Exposed to Nicotine During Adolescence.
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C. **Publications**

Bolaños, C. A., Willey, M. D., Maffeo, M. L., Powers, K. D., Kinka, D. W., Grausam, K. B., & Henderson, R. P. (2008). Antidepressant treatment can normalize adult behavioral deficits induced by early-life exposure to methylphenidate. *Biological Psychiatry, 63(3),* 309-16

D. **Works Submitted**

Bukach, C. M., Vickery, T., Kinka, D., & Gauthier, I. Training experts: Individuation without naming is worth it.

E. **Presentations**

Kinka, D., Grovola, M. R., & Bukach, C. (2009). Does shared dimensionality inhibit object recall? Society for Neuroscience annual conference, Chicago, IL.

Kinka, D., Bukach, C., Gauthier, I. (2009). Are label association necessary for the acquisition of expertise? Vision Sciences Society annual conference, Naples, FL.

Kinka, D., Grovola, M., Bukach, C. (2009). The effect of shared dimensionality on object recall. University of Richmond Arts & Sciences, graduate symposium, Richmond, VA.

Kinka, D., Grovola, M., Bukach, C. (2009). The effect of shared dimensionality on object recall. College of William & Mary Arts & Sciences, graduate symposium, Williamsburg, VA.

Butt, E. W., Ubiwa, J., Kinka, D., Bukach, C. (2009). The effect of attitude on the other race effect. Southeastern Psychological Association annual conference, New Orleans, LA.

Bolaños, C. A., Kinka, D. W. (2008). Effects of adult treatment with nicotine and the antidepressant fluoxetine on male rats exposed to nicotine during adolescence. ACC Meeting of the Minds Conference, Tallahassee, FL.

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F. **Grants**

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G. **Projects Underway**

Kinka, D., Roberts, K., & Bukach, C. The interaction of structural and conceptual information determines object confusability.

Kinka, D., & Bukach, C. Shared features and similarity: Implications for category specificity and normal object recognition (*Masters Thesis*).

H. **Professional Positions**

1. Research Assistant • Clark-Hill Institute for Positive Youth Development • Virginia Commonwealth University • Part-time position • Fall 2008 – Winter 2009

   Duties: Participant recruitment, conducting personal interviews and administration of survey materials.

   Supervisors: Anne Y. Greene, Jennifer Elswick, Dana Andrews

2. Directed Individual Study • Florida State University • Part-time position • Fall 2006 – Spring 2007

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I. Professional Activities

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    a. Cognitive Neuroscience • University of Richmond • Spring 2010
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2. Meeting Attended:

    a. Society for Neuroscience Annual Meeting • Chicago, IL • November 2009
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    c. Vision Sciences Society (VSS) annual meeting • Naples, FL • May 2009
    d. Southeastern Psychological Association (SEPA) annual meeting • New Orleans, LA • March 2009
    e. Society for Neuroscience Annual Meeting • San Diego, CA • November 2007

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